CYBERBETICS AND SYSTEMS RESEARCH 2

Proceedings of the Seventh European Meeting on Cybernetics and Systems Research, organized by the Austrian Society for Cybernetics Studies, held at the University of Vienna, Austria, 24-27 April 1984

Edited by

Robert TRAPPL

University of Vienna
Austria

Editorial Board

G. Broekstra, W. Buchstaller, C. Carlsson, A. Ghosal, F. de P. Hanika, W. Horn, H. Huebner, G. J. Klir, Y. Kodratoff, G. Majone, H. Maurer, B. Z. Nizetic, G. Pask, P. K. M'Pherson, F. Pichler, W.-D. Rauch, J. Retti, L. M. Ricciardi, W. Wahlster, A. Wierzbicki.

1984

NORTH-HOLLAND
AMSTERDAM · NEW YORK · OXFORD

©Elsevier Science Publishers B.V., 1984

All rights reserved. No part of this publication may be reproduced, stored in a retrieval system, or transmitted, in any form or by any means, electronic, mechanical, photocopying, recording or otherwise, without the prior permission of the copyright owner.

ISBN: 0 444 86898 4

Publishers:
ELSEVIER SCIENCE PUBLISHERS B.V.
P.O. Box 1991
1000 BZ Amsterdam
The Netherlands

Sole distributors for the U.S.A. and Canada:
ELSEVIER SCIENCE PUBLISHING COMPANY, INC.
52 Vanderbilt Avenue
New York, N.Y. 10017
U.S.A.

Library of Congress Cataloging in Publication Data

European Meeting on Cybernetics and Systems Research
(7th : 1984 : University of Vienna)
Cybernetics and systems research 2.

1. Cybernetics--Congresses. 2. System theory--Congresses. 3. Systems engineering--Congresses. 4. Biomedical engineering--Congresses. I. Trappl, Robert. II. Österreichische Studiengesellschaft für Kybernetik. III. Title. IV. Title: Cybernetics and systems research two.
Q300.E88 1984 001.53 84-4073
ISBN 0-444-86898-4 (U.S.)

PRINTED IN THE NETHERLANDS

PREFACE

Opening Address by the Chairman of the Meeting

When I was a boy of 4 or 5 years, I used to play a strange play with my small toy figures: Delegations arrived at a castle, servants bowed, the leader, mostly a duke, bowed, and then they were led to the king in a special walking sequence. Arriving there, the aristrocrats, in a strict hierarchical order, bowed to the duke, until the king and the duke bowed to each other.

What made me perform these rituals? Sure not my upbringing in a poor family. As I see it now: While the world was in turmoil, my father serving at the frontier, my mother and I seeking shelter, often several times a day, during air-raids; in this - not only for a child - unintelligible world, I constructed my own one, with laws I created and with rituals I could understand.

The biennial European Meeting on Cybernetics and Systems Research, a ritual? Convened for the first time in 1972 in Vienna and always - with one exception - held in Vienna. Immediately after the meeting, a small group of scientists and practitioners sitting down to prepare the next meeting: Symposia titles are discussed, scientists are invited to chair symposia, the Federal Ministry of Science and Research is asked to support the meeting financially, and so on, all in all 118 items on my agenda list.

On my shelves I can see the proceedings of all meetings: 2 volumes, bound in white (now slightly yellow) card boards, published by Transcripta Books, London; 11 volumes in different, beautiful colours published by Hemisphere Publishing Company, Washington, D.C.; and 1 volume in green cloth binding, from North-Holland Publishing Company, Amsterdam. The names in them: Some scientists died in the meantime (e.g. Professor Margaret Mead, plenary lecturer in our first meeting, Professor Boulanger, co-chairman of the first meeting), but many scientists acting as speakers or even chairmen through many or even all meetings. And the topics: Most of the symposia about the same topics as in 1972, the only major change being the introduction of an Artificial Intelligence symposium.

I wonder whether these European Meetings have become a ritual, for us, when preparing it, for you, when attending it. Do we use it to protect us from a world in turmoil? Does it reflect the changes in the world during these 12 years? And do the papers we present mirror at least partially the problems mankind is facing?

I have no answer. Please help us to decide how or if at all we shall continue. Thank you.

ROBERT TRAPPL

PATRONS

Dr. Heinz Fischer
Federal Minister of Science and Research

Leopold Gratz
Mayor of the City of Vienna

Magn. Professor Dr. Hans Tuppy
Rektor of the University of Vienna

CHAIRMAN

Professor Dr. Robert Trappl
President, Austrian Society for Cybernetics Studies

SPONSORS

Federal Ministry of Science and Research
Municipality of Vienna
Vienna Tourist Board

PROGRAMME COMMITTEE

Professor B. Banathy (USA)
Professor G. Broekstra (Netherlands)
Professor C. Carlsson (Finland)
Professor W.W. Gasparski (Poland)
Professor R. Glanville (UK)
Professor F. de P. Hanika (UK)
Dr. W. Horn (Austria)
Professor N. Hu (China)
Professor G.J. Klir (USA)
Professor Y. Kodratoff (France)
Professor A. Lee (UK)
Professor H. Maurer (Austria)
Professor J.G. Miller (USA)
Professor B.K. M'Pherson (UK)
Professor B.Z. Nizetic (Denmark)
Professor M. Nowakowska (Poland)
Professor G. Pask (UK)
Professor M. Peschel (GDR)
Professor F. Pichler (Austria)
Professor Cheng Quian-sheng (China)
Professor W.-D. Rauch (FRG)
Dipl.-Ing. J. Retti (Austria)
Professor L.M. Ricciardi (Italy)
Dr. N. Rozsenich (Austria)
Professor R. Trappl (Austria)
Dr. H. Trost (Austria)
Acad. Ya. Tsypkin (USSR)
Professor R. Vallée (France)
Professor W. Wahlster (FRG)
Professor A. Wierzbicki (Poland)
Professor G. de Zeeuw (Netherlands)

ORGANIZING COMMITTEE

I. Bodirsky
Dipl.-Ing. E. Buchberger
Dr. W. Buchstaller
Professor F. de P. Hanika
Dr. W. Horn
Professor H. Huebner
G. Knittel
Dr. O. Ladanyi
P.E. Martin
Professor F. Pichler
E. Plechl
Professor W.-D. Rauch
Dipl.-Ing. J. Retti
U. Stadler
Dipl.-Ing. I. Steinacker
Professor R. Trappl
Dr. H. Trost
A. Yodzis
S. Wiesbauer

LIST OF CONTENTS

此为试读，需要完整PDF请访问：www.ertongbook.com

SYSTEM AND DECISION THEORY

Chairpersons: F. Pichler (Austria)
A. Wierzbicki (Poland)

CYBERNETICS IN BIOLOGY AND MEDICINE

Chairperson: L.M. Ricciardi (Italy)

CYBERNETICS IN ORGANIZATION AND MANAGEMENT

Chairpersons: F. de P. Hanika (UK)
H. Huebner (Austria)
P.K. M'Pherson (UK)

ARTIFICIAL INTELLIGENCE

Chairpersons: W. Horn (Austria)
Y. Kodratoff (France)
W. Wahlster (FRG)

此为试读，需要完整PDF请访问： www.ertongbook.com

GENERAL SYSTEMS METHODOLOGY

Chairpersons:
G. J. Klir (U.S.A)
G. Broekstra (The Netherlands)

Cybernetics and Systems Research 2, R. Trappl (ed.)
© Elsevier Science Publishers B.V. (North-Holland), 1984

POSSIBILISTIC INFORMATION THEORY[1]

George J. Klir

Department of Systems Science
Thomas J. Watson School of Engineering, Applied Science, and Technology
State University of New York at Binghamton
Binghamton, New York 13901 U.S.A.

It is argued that a new measure of information, defined within the framework of possibility theory, is a natural generalization of the Hartley information. In addition, this measure also possesses possibilistic counterparts of all properties of the Shannon information. It is envisioned that a theory based on the possibilistic information, when properly developed, will be an important tool in dealing with systems which involve uncertainty that is not statistical in nature.

It is well known that the amount of information obtained by observing the actual outcome of an experiment involving a finite set of alternative outcomes (events, states, etc.), say set X, can be measured by the uncertainty associated with the prospective outcome before the experiment [11,27,44]. A measure of uncertainty, when adopted as a measure of information, does not include semantic and pragmatic aspects of information. As such, it is not adequate for dealing with information in human communication [17]. However, for dealing with structural (syntactic) aspects of systems, such a measure is not only adequate but even desirable [3-8,10,31]. In fact, it can be directly used for measuring the degree of constraint among variables of interest, representing thus a powerful tool for dealing with systems problems such as systems modelling, analysis, or design [12-15,19-21,25,39].

The first measure of information was derived by Hartley in 1928 [32]. Requiring that

(i) the amount of information be proportional to the number of possible outcomes under consideration, and

(ii) whenever the numbers of selections from two sets of possible outcomes are such that the number of possible sequences of outcomes is the same for both of them, then the amount of information be also the same for both,

Hartley showed that the amount of information $I(n)$ necessary to characterize an outcome of a finite set with n outcomes must have the form

$$I(n) = K \log_b n, \qquad (1)$$

where $K>0$ and $b>1$ are arbitrary constants, which determine the size of the unit of information. Usually, the information is measured in bits and, then,

$$I(n) = \log_2 n. \qquad (2)$$

The measure $I(n)$, referred to as the Hartley information, was further studied by Renyi [41]. He proved that (1) is the only class of functions that satisfy the following two requirements (axioms):

(I1) $I(n \times m) = I(n)+I(m)$ for $n,m=1,2,\ldots$;
(I2) $I(n) \le I(n+1)$.

According to requirement (I1) (additivity), if a set with $n \times m$ outcomes can be partitioned into n subsets, each with m outcomes, then we should be able to proceed in two steps to characterize a particular outcome of the full set. First, we determine that subset to which the outcome in question belongs; the required amount of information is $I(n)$. Next we characterize the outcome within the determined subset; the required amount of information is now $I(m)$. The two amounts of information completely characterize the outcome of concern.

According to requirement (I2) (monotonicity), the larger the set, the more information it represents.

When an appropriate normalization requirement

(I3) $I(2) = 1$

is added to the requirement (I1) and (I2), the unique function (2) is implied.

In 1948, an alternative measure of information based on uncertainty was formulated by Shannon in terms of probability theory [42]. The measure, usually referred to as Shannon information (or Shannon entropy), is expressed by the function

$$H(f(x) \mid x \in X) = - \sum_{x \in X} f(x) \log_2 f(x), \qquad (3)$$

where $f(x)$ denotes probabilities of outcomes x in a finite set X. It is well known that (3) is the only function that satisfies the following requirements, generally accepted as

8650113

necessary for every meaningful measure of uncertainty (or information) defined within the framework of probability theory (except for the normalization requirement by which the unit of information is defined):

(H1) symmetry--uncertainty is invariant with respect to permutations of probabilities;

(H2) expansibility--when outcomes with zero probabilities are added to the considered set of outcomes, the uncertainty does not change;

(H3) subadditivity--the uncertainty of a joint probability distribution is not greater than the sum of the uncertainties of the corresponding marginal probability distributions;

(H4) additivity--for probability distributions of any two independent sets of outcomes, the uncertainty of the joint probability distribution is equal to the sum of the uncertainties of the individual probability distributions;

(H5) continuity--uncertainty is a continuous function in all its arguments.

(H6) normalization--$H(0.5,0.5) = 1$.

Shannon measure of information was considered for many years as the only feasible base for developing information theory. Although it was originally introduced for the purpose of analyzing and designing telecommunication systems, it became later obvious that its significance and applicability reaches far byyond this original purpose. Its important role in measurement, prediction, retrodiction, deduction, induction, pattern recognition, and other scientific procedures was recognized by Brillouin [11], Watanabe [45], Jaynes [36,37], and others [9,18,30,36,40]; its role as a fundamental and general tool for investigating and designing systems of a universal nature was first demonstrated by Ashby [3-7] and later by Conant [19-23] as well as others [12-15,25,39].

Notwithstanding the significance and success of the current information theory based on the Shannon entropy, it is becoming increasingly clear that the probabilistic framework within which the theory is developed is ill-suited for many applications that have come to fore in recent years. In particular, it is ill-suited for dealing with problems that were characterized by Warren Weaver as problems of organized complexity [46]. As relationships in society become more complex, due to advances in modern technology, the significance of this range of problems increases. At the same time, technology provides us with a new tool--the computer--by which we can meaningfully enter into this neglected area. The reason why traditional methods are inadequate to handle this level of complexity in systems is that these systems are rich in factors that cannot easily be justified as negligible, but, on the other hand, they are not sufficiently complex and random to yield meaningful statistical averages. Thus, they are not susceptible to either of the two simplification strategies, exemplified by Newtonian Mechanics and Statistical Mechanics, invented by science.

When the complexity of an organized system increases, the ability to make precise and yet relevant statements about its behavior diminishes. One way of dealing with complex systems that possess the characteristics of organized complexity, perhaps the most significant one, is to allow imprecision in describing properly aggregated data. Here, the imprecision is not of a statistical nature, but rather of a more general modality, even though it may include imprecise statistical descriptions as well. The mathematical apparatus for this new modality, which is recognized under the name "theory of fuzzy sets," has been under development since the mid-1960's [24,27]. For reasons mentioned previously in the context of probability theory, it is desirable to develop an adequate information theory within this new framework. Although the amount of information should still be measured by the amount of uncertainty associated with a given situation, the uncertainty is now of a different nature within the new framework of fuzzy set theory.

One significant area of fuzzy set theory is a theory of possibility. Its functions were formulated by Zadeh in 1978 [48]. He introduced the concept of a possibility distribution and possibility measure, the latter being a special case of the concept of fuzzy measure proposed by Sugeno [43].

A possibility measure defined on a finite set X is a function

$$\pi: P(X) \to [0,1]$$

that is uniquely determined by a possibility distribution function

$$f: X \to [0,1]$$

via the formula

$$\pi(A) = \max_{x \in A} f(x),$$

where $A \subseteq X$. A possibility distribution

$$\underline{f} = (f(x) \mid x \in X)$$

is called a normalized possibility distribution if and only if

$$\max_{x \in X} f(x) = 1.$$

To develop an alternative information theory, based on possibility theory rather than probability theory, a new conception of information must be used; it may conveniently be referred to as possibilistic information. In analogy with its probabilistic counterpart, possibilistic information should be defined in terms of the underlying notion of possibilistic uncertainty.

A measure of uncertainty for possibility theory was discovered jointly by Higashi and Klir in 1982; its derivation and basic properties are described in a recent paper [33]. In order to define this measure, the following two concepts for possibility distributions must be first introduced:

1. For each possibility distribution

$$\underline{f} = (f(x) \mid x \in X)$$

defined on a finite set X and for each $\ell \in [0,1]$, let

$$c: F_X \times [0,1] \to P(X),$$

where F_X denotes the set of all possibility distributions on X and let c be a function such that

$$c(\underline{f},\ell) = \{x \in X \mid f(x) \geq \ell\}.$$

This function is called an ℓ-cut function and the set is called an ℓ-cut of $\underline{f}$.

2. Let $\underline{f} = (f(x) \mid x \in X)$ be a possibility distribution on X. Then,

$$L_{\underline{f}} = \{\ell \mid (\exists x \in X)(f(x) = \ell \text{ or } \ell = 0)\}$$

is called a level set of $\underline{f}$. Let

$$L_{\underline{f}} = \{\ell_1, \ell_2, \ldots, \ell_r\}$$

denote the level of $\underline{f}$, $\ell_1 = 0$, $r = |L_{\underline{f}}|$, and $i<j$ implies $\ell_i < \ell_j$.[2] For convenience, let

$$\ell_{\underline{f}} = \max_{x \in X} f(x).$$

Clearly, $\ell_{\underline{f}} = \ell_r \in L_{\underline{f}}$.

The measure of possibilistic uncertainty (and information), referred to as the U-uncertainty, is a function

$$U: F \to [0,\infty],$$

where F is the set of all possibility distributions defined on finite sets except the distributions (0,0,...,0), such that

$$U(\underline{f}) = \frac{1}{\ell_{\underline{f}}} \sum_{k=1}^{r-1} (\ell_{k+1} - \ell_k) \log_2 |c(f,\ell_{k+1})|, \quad (1)$$

or, using a different notation,

$$U(\underline{f}) = \frac{1}{\ell_{\underline{f}}} \int_0^{\ell_{\underline{f}}} \log_2 |c(\underline{f},\ell)| \, d\ell. \quad (2)$$

The distribution (0,0,...,0) is excluded since it is not meaningful to consider a set of alternatives none of which is possible.

The U-uncertainty, in agreement with the Shannon entropy, possesses the possibilistic counterparts of all the properties required for a measure of uncertainty: symmetry, expansibility, subadditivity, additivity, continuity, and normalization. The proof for this can be found in the mentioned paper [33]. In addition, U-uncertainty has an important property of monotonicity: if two possibility distributions $\underline{f}_1$ and $\underline{f}_2$ defined on the same set X are such that $\underline{f}_1 \leq \underline{f}_2$ (i.e., $f_1(x) \leq f_2(x)$ for all $x \in X$) and

$$\max_{x \in X} f_1(x) = \max_{x \in X} f_2(x),$$

then $U(\underline{f}_1) \leq U(\underline{f}_2)$.

It is significant that the possibilistic information based on the U-uncertainty is a natural generalization of the Hartley information. This is not true for the Shannon information, which does not satisfy the monotonicity of the Hartley information.

The U-uncertainty can be viewed as the mean of uncertainties for all ℓ-cuts associated with the respective level set (each expressed by the Hartley measure), weighted by differences in the levels. It is obvious that formula (1) can be rewritten as

$$U(f) = \frac{1}{\ell_r}\left[\ell_r \log_2 |c(f,\ell_r)| + \sum_{k=1}^{r-1} \ell_{r-k} \log_2 \frac{|c(f,\ell_{r-k})|}{|c(f,\ell_{r-k+1})|}\right] \quad (3)$$

The first term in (3) represents the Hartley information associated with the set of outcomes that have the highest possibility degree $\ell_r = \ell_f$ ($\ell_r = 1$ if the possibility distribution involved is normalized); each of the remaining terms represents the Hartley information associated with the set of outcomes whose possibility degree is ℓ_{r-k} $(k=1,2,\ldots,r-1)$, weighted by the ratio of ℓ_{r-k} to ℓ_r (or by the value ℓ_{r-k} in the normalized case).

To reconcile the Hartley information (which is not continuous) with the Shannon information (which is not monotonic), the former has frequently been given one of two probabilistic interpretations. In one, it is viewed as a special case of the Shannon

此为试读，需要完整PDF请访问：www.ertongbook.com