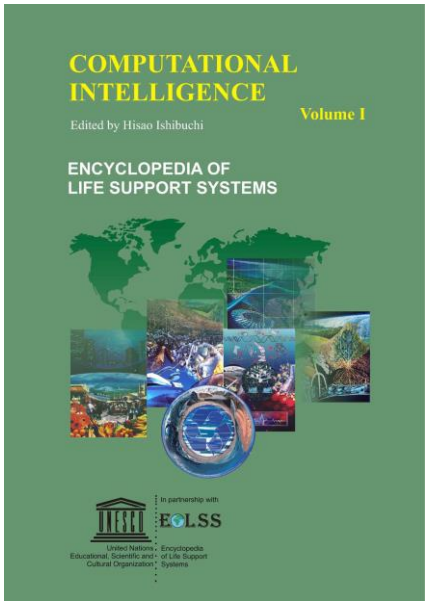
COMPUTATIONAL INTELLIGENCE



Computational Intelligence - Volume 1

No. of Pages: 400

ISBN: 978-1-78021-020-9 (eBook)
ISBN: 978-1-78021-520-4 (Print Volume**)**

Computational Intelligence - Volume 2

No. of Pages: 410

ISBN: 978-1-78021-021-6 (eBook)
ISBN: 978-1-78021-521-1 (Print Volume**)**

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