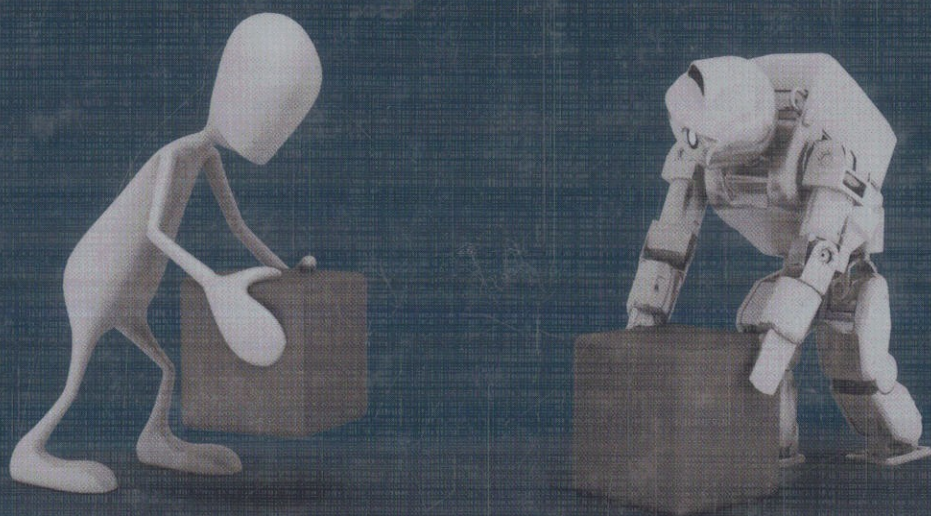


ENGINEERING SCIENCES

Micro- and Nanotechnology

ROBOT PROGRAMMING BY DEMONSTRATION: A PROBABILISTIC APPROACH

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