<u>Topic</u>	PP		
• \Box (title)	1		
• 🗆 length			
IEEE standard double-column format (6 pages normally and 10 pages maximum)			
6pp = 5000ww (Word): 25–50¶¶ (40–83 for 10pp) 100-200 w/¶ (figure 200)			
• 🗆 Abstract	1		
• \Box (text)	46		
• 🔲 I. Introduction	5		
• \Box A. Expanding the Concept of Computation	3		
• [] 1. We are approaching the limits of digital electronics and the von Neumann architecture, so we need to develop new computing technologies and methods of using them.	1		
• \square 2. Neural networks and similar applications show the need for analog computation.	1		
• 3. Nature gives many examples of unconventional computation.	1		
• B. Exploiting Novel Materials & Processes	2		
• □ 1. New materials may be used, but they present challenges, such as difficulty in structuring them for computing and high error/defect rates.	1		
• 2. Our goal should be to match computational processes to the physical processes most suited to implement them.	1		
• 🔲 II. Generalized Computation	4		
• \Box A. Why a general definition is needed	1		
• [1] 1. We do not want to limit our options by beginning with too narrow a definition of computation.	1		
• \square B. The definition	2		
• □ 1. The purpose of a <i>computational system</i> is the mathematical manipulation of mathematical objects.	1		
• 2. A computational process can be <i>realized</i> by any physical system that can be described by the same mathematics.	1		
• $\Box C.$ Goal	1		
• 1. My goal is a model of generalized computation that can be implemented in a wide variety of physical processes.	1		
• 🗆 III. Representation of Data	18		
• 🗆 A. Urysohn Embedding	8		
• 1. Problem: How do we represent quite general mathematical objects on a physical system?	1		

٠	🗆 III. Rep	presentation of Data	18
<u>Topic</u>	• 🗆 A. U	rysohn Embedding	¶¶.8
	• 🗆 1.	Problem: How do we represent quite general mathematical objects on a physical system?	1
	• 🗆 2.	Continua can be embedded in Hilbert spaces (Urysohn)	1
	• 🗆 3.	An epsilon-mesh defines a convenient base.	1
	• 🗆 4.	As usual, finite-precision approximations can be used.	1
	• 🗆 5.	Discrete spaces (for generalized digital computation) can be embedded in continua.	1
	• 🗌 6.	The representation can make use of the discrete set of Fourier coefficients, which is like a layer in a neural net.	1
	• 🗌 7.	Some generalized computers may operate directly on the function space (of fields) as a representation.	1
	• 🗌 8.	A finite set of coefficients corresponds to band-limited fields.	1
	• 🗆 B. Ar	n Abstract Cortex	5
	• 🗆 1.	The memory of general-purpose computer should be an unstructured medium that can be programmatically structured into multiple variables.	1
	• 🗆 2.	A field can be subdivided into subfields, representing different field variables.	1
	• 🗆 3.	Similarly, a discrete set of coefficients can be partitioned.	1
	• 🗆 4.	This is analogous to the definition of areas in the cortex, which can serve as a model for memory structuring in the U-machine.	1
	• 🗆 5.	Direct products of continua can be handled simply.	1
• \Box C. Transduction		5	
	• 🗆 1.	Physical spaces are almost always vector spaces (other continua are mostly useful for internal variables).	1
	• 🗆 2.	Input	2
	•	(a) Input transductions are analogous to receptive fields of sensory neurons.	1
	•	(b) Often they will be simple RBFs or linear transformations.	1
	• 🗆 3.	Output	2
	•	(a) Physical output spaces are virtually always vector spaces, and so outputs usually can be generated by linear superposition.	1
	•	(b) More generally, we invert the embedding of the output variable.	1
٠	□ IV. Rep	presentation of Process	17
	• 🗆 A. M	fultivariate Interpolation	5
	• 🗆 1.	Transformations on continua are replaced by functions on Hilbert spaces.	1
	• 🗆 2.	Multivariate interpolation based on linear combinations of nonlinear basis functions can be used for general computation.	1

 IV. Representation of Process A. Multivariate Interpolation 	17 5
• 2. Multivariate interpolation based on linear combinations of nonlinear be functions can be used for general computation.	basis 1 ¶¶
• 🗆 3. For example, an RBF network (or other universal approximator) can general-purpose computation.	be used for 1
• 🗌 4. For unknown functions, RBF training can be used.	1
 5. For known functions, weights can be computed and set directly (if ph feasible), or RBF training can be used. 	nysically 1
• 🗆 B. Decomposing Processes	4
• 🔲 1. Description of feed-forward and feedback processes.	1
 	to table 1 npositions
• 🗆 3. Optimal computations of standard functions can be provided in librar	ies. 1
 	alog 1
• C. Programming Methods	4
 1. The U-machine is divided into a variable (data) space and a function (space. 	(program) 1
• \Box 2. If the function space is 3D, then arbitrary interconnections can be acc	complished. 1
• 🗆 3. In many cases training can be accomplished by accessing only the inpotent output variables (not the weights).	put and 1
• 4. The exact methods of programming the weights will depend on the pl medium, but might be analogous to FPGA programming.	hysical 1
• D. Analogies to Neural Morphogenesis	4
• 1. The variable space corresponds to neural grey matter (cortex) and the space to (axonal) white matter.	function 1
• 2. Signals applied to variable areas can be used to guide projections from the other.	n one to 1
• 3. Weights are programmed by training with complete patterns, or by paindividual Fourier coefficients or basis functions.	airs of 1
• \Box 4. Connections do not have to be perfect.	1
• 🗆 V. Conclusions	2
• \square A. In summary, the U-machine provides a model of generalized computation can be applied to massively-parallel paracomputation in bulk materials	on, which 1
 B. Future work will explore alternative embeddings and interpolation methods well as widely applicable techniques for creating interconnections. 	nods, as 1
• 🗆 References	
• \Box 1. (citation)	