Revised August 1987

UNITIZED RECOGNITION CODES FOR PARTS AND WHOLES: THE UNIQUE CUE IN CONFIGURAL DISCRIMINATIONS

by

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In M.L. Commons, R.J. Herrnstein, S.M. Kosslyn, and D.B. Mumford (Eds.)
Computational and Clinical Approaches to Pattern Recognition and Concept Formation
Hillsdale, NJ: Erlbaum Associates, 1990

† Supported in part by the National Science Foundation (NSF IRI-84-17756) and the Office of Naval Research (ONR N00014-83-K0337).

‡ Supported in part by the Air Force Office of Scientific Research (AFOSR 85-0149) and the National Science Foundation (NSF IRI-84-17756).

Acknowledgements: We wish to thank Cynthia Suchta for her valuable assistance in the preparation of the manuscript and illustrations.

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Emergence of the Unique Cue in Configural Discriminations

A number of conditioning studies have analyzed how associative strengths of stimuli combine when they are presented in compounds. Results from these studies suggest, on the one hand, that stimulus compounds should be viewed as configurations, or groupings, in their own right, yet on the other hand, also indicate that summation of the effects of separately trained stimuli can occur. For example, in a negative patterning procedure, two stimuli, A and B, are reinforced when presented separately, but not when presented in compound. Such A+, B+, AB- training can lead to responding to A and B when each is presented alone but not to the AB compound (Kehoe & Gormezano, 1980). By contrast, animals that receive only A+ and B+ training may respond more to the AB compound than to A and B separately, even if the levels of responding to A and B are matched in the two training procedures (Rescorla, 1972, 1973; Whitlow & Wagner, 1972).

In conditional discrimination experiments, animals are presented with two stimulus compounds that are reinforced (AC+ and BD+) and two that are not reinforced (AD- and BC-). Thus each of the elements A, B, C, and D is reinforced on half of its presentations. Despite this fact, the reinforced configurations elicit responding but the others do not (Rescorla, Grau, & Durlach, 1985; Saavedra, 1975).

These studies are illustrative of a large conditioning and cognitive literature that implicates the existence of recognition codes wherein multiple groupings, or chunks, of input information can be processed simultaneously. Properties of such recognition codes are described below in a general cognitive setting.

Multiple Groupings or Chunks in Unitized Recognition Codes

The chapter by Carpenter and Grossberg (this volume) describes one line of our group's recent progress towards characterizing the self-organization of sensory and cognitive recognition codes using the principles and mechanisms of adaptive resonance theory. The present chapter describes a parallel line of work. In Carpenter and Grossberg (this volume), an input pattern to level F_1 is globally grouped at F_2 when the F_2 population that receives the maximal input from the $F_1 \rightarrow F_2$ adaptive filter is chosen for short-term memory (STM) storage. Within the total architecture of an adaptive resonance attentional-orienting system, this simple type of F_2 reaction to the $F_1 \rightarrow F_2$ adaptive filter leads to powerful coding properties. On the other hand, at least two major facts show that a level F_2 which makes global choices must be viewed as a special case of a more general design for F_2.

If the second processing stage F_2 made a choice, then later processing stages that are activated by F_2 alone could not further analyse the input pattern across F_1. Such further processing stages would therefore be redundant. The coding hierarchy for individual input patterns would end at the choice, or global grouping, stage. This conclusion does not preclude the possibility that globally grouped individual events embedded in regularly occurring temporal lists generate unitized representations of these lists at a higher coding level (Cohen & Grossberg, 1986, 1987; Grossberg, 1985; Grossberg & Stone, 1986).

By contrast, a coding scheme wherein F_2 generates a spatially distributed representation of the F_1 activity pattern, rather than a choice, could support subsequent levels $F_3, F_4, \ldots, F_n$ for coding multiple groupings, or chunks, and thus more abstract invariants of an input pattern. This possibility raises many issues concerning the properties of these configurations and their invariants, and of the architectural constraints that enable a multi-level coding hierarchy to learn and recognize distributed invariants in a stable and globally self-consistent fashion.

Unitized Coding of Parts and Wholes in Speech, Visual Object Recognition, and Cognition

The type of circuit design from which F_2—and by extension higher levels $F_3, F_4, \ldots, F_n$—may be fashioned is one whose properties are of equal value for visual object recognition, speech recognition, and higher cognitive processes. Indeed, the same circuit design is important wherever spatially distributed self-organizing recognition codes are used. This type of parallel neural architecture is called a *masking field* (Cohen & Grossberg, 1986, 1987; Grossberg, 1978, 1984, 1986; Grossberg & Stone, 1986). A masking field is a multiple scale, self-similar, automatically gain-controlled cooperative-competitive feedback network. The purpose of a masking field is to simultaneously detect, and weight properly in STM, all of the salient parts, or groupings, of an input pattern, including possibly the pattern as a whole, and predicted future patterns of which the present pattern forms a part. Thus a masking field generates a spatially distributed, yet unitized, representation of the input pattern in STM. The type of problem which a masking field solves is clarified by considering how a complex time series, such as speech, is decoded by an experienced observer.

One of the fundamental problem areas in speech and language research, cognitive psychology, and artificial intelligence is the characterization of the functional units into which speech sounds are integrated by a fluent speaker. A core issue is the *context sensitivity* of these functional units, or the manner in which the perceptual grouping into functional units can depend upon the spatiotemporal patterning of the entire speech stream. Such context sensitivity is evident on every level of speech and language organization. For example, words such as Myself, Inspire, Become, and Forbid are each composed of parts which have very different meanings. A critical problem in speech research concerns the manner in which a word, as a whole, can generate a different code than its parts, and can therefore access a different meaning. Thus, although a word such as Myself is used by a fluent speaker as a unitized verbal chunk, in different verbal contexts, My, Self, and Elf are all words in their own right with their own different meanings. Although an utterance which ended with My would generate one grouping of the speech flow, an utterance which went on to include the entire word Myself could supplant this encoding with one appropriate to the longer word. Thus, in order to understand how context-sensitive language units are perceived by a fluent speaker, one must explain how all possible groupings of the speech flow are analysed through time, and how certain groupings can be chosen in one context without preventing other groupings from being chosen in a different context. The same problem must be solved, albeit with more abstract codes, on every level of cognitive processing.

The functional units into which a fluent language user groups a speech stream are dependent upon the observer's prior language experiences. For example, a learned code, or unitized representation, for the word Myself does not exist in the brain of a speaker who is unfamiliar with this word. Thus an adequate theory of how an observer parses a speech stream, or other temporally evolving event stream, into context-sensitive cognitive units needs to explain how developmental and learning processes, notably long term memory (LTM) processes, bias the observer to experience some perceptual groupings over others. Within the present theory, such biasing takes place within the LTM traces of bottom-up adaptive filters and top-down learned expectations (Carpenter & Grossberg, this volume).

The same considerations hold when words such as Myself are presented visually, rather than auditorily. Then the problem becomes one of visual object recognition and of figure-ground segmentation. The problem exists also on a finer level of visual processing, since letters such as E contain, as parts, components such as L and F. The masking field design is capable of sensing multiple pattern groupings, which subtend multiple spatial scales, and assigns each of these groupings its proper STM coding weight. The masking field thus offers an alternative approach to the one described by Mumford (this volume) for providing a structural description of temporally or spatially patterned information.

Developmental Rules Imply Cognitive Rules as Emergent Properties of Neural Network Interactions

It has been shown how a masking field network can arise through simple rules of neuronal growth (Cohen & Grossberg, 1986; Grossberg, 1986). These rules include random growth of connections along spatial gradients from F_1 to F_2, activity-dependent cell growth within F_2, and competition for conserved synaptic sites within F_2 (Figure 1a). Thus the masking field provides an example of how simple rules of neuronal development can give rise to a system whose emergent properties act *as if* it obeys complex rules of context-sensitive cognitive coding.

place Figure 1 here

The masking field network F_2 selects its unitized representations by performing a new type of multiple scale analysis of distributed activity patterns across its input level F_1. Network F_2 is activated by an adaptive filter $F_1 \rightarrow F_2$ that transforms the activity pattern across F_1 into an input pattern to F_2. Such a network F_2 acts as a content-addressable memory. Network F_2 selects compressed (unitized, chunked) recognition codes that are predictive with respect to the activation patterns flickering across the feature detectors of F_1, and competitive inhibits, or masks, codes which are unpredictive with respect to the F_1 patterns. The individual nodes of F_1 represent *items* in the temporal sequence, or list, of events that perturb F_1. Such a list of items generates the total activity pattern across F_1 at any time. Individual F_2 nodes are sensitive to patterns of F_1 activation and thus to contextual information about the list of items that is perturbing F_1. Consequently, the activity patterns across F_2 are called *list codes in STM*. Thus the units of F_1 and F_2 are items and lists, not letters and words, as in the McClelland and Rumelhart (1981) interactive activation model. See Grossberg (1984, 1986, 1987) for a discussion of the issues and data relevant to this issue.

A masking field F_2 can simultaneously detect multiple groupings within the input patterns received by F_1 and assign activation weights to the codes for these groupings which are predictive with respect to the contextual information embedded within the patterns and the prior learning of the system. A masking field automatically rescales its sensitivity as the overall size of an input pattern changes, yet also remains sensitive to the microstructure within each input pattern. Due to its automatic rescaling, the masking field network does not confuse "wholes" with their "parts," yet enables familiar "parts" to emerge as "wholes" in their own right in an appropriate input context, just as events A and B may be processed individually if they are presented separately or as a compound AB with multiple parts when presented together. Otherwise expressed, the spatial patterning of enhanced STM activities across F_2 embodies a hypothesis about the input stream across F_1. As will be described in greater detail below, this hypothesis-testing code can predict, or anticipate, subsequent events by assigning activities to groupings which have not yet fully occurred, based on the available evidence. Thus this hypothesis-testing mechanism acts like a real-time prediction, or evidence-gathering, machine. No serial programs or cognitive-rule structures exist within the masking field network to generate these properties. Instead, the model nodes, or neurons, obey membrane equations undergoing shunting (mass action) on-center off-surround (cooperative-competitive) recurrent (feedback) interactions (Figure 1b) that are defined below. The STM code of a masking field is an emergent property of these interactions.

Sensitivity to Multiple Scales and Intrascale Variations

The spatial analysis that is performed by a masking field is sensitive to two different types of pattern changes.

A. *Sensitivity to Multiple Pattern Scales*

As a word like Myself is processed, a subword such as My occurs before the entire word Myself is experienced. Figure 2a schematizes this type of informational change. As the word is presented, earlier STM activations of the item representation within F_1 are modified and supplemented by later STM activations. The STM pattern across F_1 expands as the word is presented. After Myself is fully stored within F_1, parts such as My, Self, and Elf are still (at least partially) represented within the whole. The masking field F_2 can nonetheless update its initial response to My as the remainder of Myself is presented. In this way, the masking field can react to the whole word rather than only its parts.

place Figure 2 here

B. *Sensitivity to Internal Pattern Miscrostructure*

The second type of masking field sensitivity is illustrated by the two words Left and Felt. This comparison is merely illustrative. It does not attempt to characterize the many subtle context-sensitive alterations that occur in evolving sound patterns or reading patterns. The words Left and Felt illustrate the issue that the same *set* of item representations within F_1 may be activated by different item *orderings*. To distinguish two such activity patterns across F_1, sensitivity within F_2 to different spatial scales of F_1 is insufficient because both lists may activate the same spatial scale of F_1. Instead, sensitivity to different STM patterns which excite the same set of items is required (Figure 2b).

Hypothesis Formation, Anticipation, Evidence, and Prediction

The dynamics of a masking field express in an abstract language a number of important intuitions about cognitive coding. Consider for definiteness a masking field F_2 that is capable of simultaneously discriminating more than one grouping within a list of events that activates F_1. For example, a masking field F_2 might respond to the F_1 representation of the word Myself by strongly activating an F_2 population that is sensitive to the whole word and weakly activating F_2 populations that are sensitive to the word's most salient parts. Or it might react to a pair of events A and B by representing the events singly and as a unitized configuration AB. In such a representation, the total STM pattern across F_2 represents the F_1 STM pattern. The relative sizes of F_2's STM activities weight the relative importance of the unitized groupings that are coded by the respective F_2 cell populations.

The suprathreshold STM activities across F_2 are approximately normalized, or conserved, due to its competitive feedback interactions (Figure 1b). The STM activities across F_2 thus function like a type of real-time probabilistic logic, or hypothesis-testing algorithm, or model of the evidence that F_2 has about the pattern across F_1.

Such a masking field also possesses a predictive, or anticipatory, capability. In response to a single item across F_1, the F_2 population that is most vigorously activated may code that item. In addition, less vigorous activations may arise among those F_2 populations that represent the most salient larger groupings of which the item forms a part. Such a masking field can anticipate, or predict, the larger groupings that may occur of which the item forms a part.

As more items are stored in STM across F_1, the set of possible groupings encoded by F_2 changes. In response to additional items, different groupings are preferred within F_2. Moreover, as more items are stored by F_1, F_2's uncertainty concerning the information represented at F_1 may decrease due to the emergence of a more constraining overall pattern. As F_2's uncertainty decreases, the spatial distribution of STM activity across F_2 becomes more focussed, or spatially localized. This type of spatial sharpening measures the degree of informational uncertainty within the F_2 code. These multiple-grouping properties of a masking field are illustrated by the computer simulations summarized in Figures 3–8.

Masking Field Equations

The differential equations for the masking field which we have simulated are

$$\begin{aligned}\frac{d}{dt}x_i^{(J)} = &-Ax_i^{(J)} + (B - x_i^{(J)})\{\sum_{j\in J} I_j p_{ji}^{(J)} z_{ji}^{(J)} + D \mid J \mid f(x_i^{(J)})\} \\ &- F(x_i^{(J)} + C)\frac{\sum_{m,K} g(x_m^{(K)}) \mid K \mid (1+ \mid K \cap J \mid)}{\sum_{m,L} \mid K \mid (1+ \mid K \cap J \mid)}\end{aligned} \tag{1}$$

and

$$\frac{d}{dt}z_{ji}^{(J)} = \epsilon f(x_i^{(J)})(-z_{ij}^{(J)} + LI_j) \tag{2}$$

where the variables $x_i^{(J)}$ are activations, or short-term memory (STM) traces, of F_2 nodes and the variables $z_{ji}^{(J)}$ are adaptive weights, or long-term memory (LTM) traces, of the pathways within the $F_1 \rightarrow F_2$ adaptive filter. The symbols J and K denote unordered sets of items at F_1. Symbols $\mid J \mid$, $\mid K \mid$, and $\mid J \cap K \mid$ denote the number of items in the respective sets J, K, and $J \cap K$. Thus $x_i^{(J)}$ is the STM trace of the ith F_2 node which receives input pathways from the set J of items at F_1.

Term $\sum_{j\in J} I_j p_{ji}^{(J)} z_{ji}^{(J)}$ in (1) denotes the total input from F_1 to node $v_i^{(J)}$ of F_2 via the adaptive filter in response to the inputs I_j across F_1. The coefficient $p_{ji}^{(J)}$ is the path strength from node v_j of F_1 to node $v_i^{(J)}$ of F_2. Term $D \mid J \mid f(x_i^{(J)})$ in (1) denotes a positive feedback signal from node $v_i^{(J)}$ to itself. Term $g(x_m^{(K)}) \mid K \mid (1+ \mid K \cap J \mid)[\sum_{m,K} \mid K \mid (1+ \mid K \cap J \mid)]^{-1}$ in (1) describes a negative feedback signal from node $v_m^{(K)}$ to node $v_i^{(J)}$. The derivation and parameter choices for these equations are found in Cohen and Grossberg (1986, 1987). In the simulations reported here, no learning was allowed to occur. Thus we chose $z_{ji}^{(J)} \equiv 1$ in equation (1) and did not use equation (2).

Computer Simulations

Figures 3–8 illustrate how presentation of a list through time can update the unitized chunks in an F_2 field that is capable of simultaneously storing several sublist groupings in STM. In Figure 3, item $\{0\}$ most strongly activates the $\{0\}$ nodes of F_2, but also weakly activates other F_2 nodes that represent groupings that include item $\{0\}$. The F_2 nodes that receive an item pathway only from $\{0\}$ have a maximal activity of .130. The F_2 nodes that receive two item pathways, including a pathway from $\{0\}$, have a maximal activity of .07. The F_2 nodes that receive three item pathways, including a pathway from $\{0\}$, have a maximal activity of .017. These activity weights characterize the degree of "evidence" that the masking field possesses that each grouping is reflected in the input pattern.

place Figure 3 here

In Figure 4, item $\{1\}$ is presented to F_1. It most strongly activates the $\{1\}$ nodes of F_2, but also weakly activates other F_2 nodes that represent groupings that include item $\{1\}$.

place Figure 4 here

In Figure 5, the $\{0, 1\}$ spatial pattern across F_1 most strongly activates a node within the $\{0, 1\}$ subfield of F_2, but also weakly activates other nodes of F_2 that receive inputs from $\{0\}$. The activity levels are .187 and .07, respectively. A comparison of Figures 3 and 4 with Figure 5 shows that F_2 can distinguish wholes from parts. Although items $\{0\}$ and $\{1\}$ form the parts of the $\{0,1\}$ F_1 pattern in Figure 5, level F_2 reacts to $\{0\}$ and $\{1\}$ as parts of the whole $\{0,1\}$ in Figure 5 very differently than it reacts to $\{0\}$ and $\{1\}$ as wholes in their own right in Figures 3 and 4. This comparison illustrates the sensitivity of a masking field to multiple spatial scales.

place Figure 5 here

The sensitivity of a masking field to the microstructure within each scale is illustrated by comparison of Figures 5 and 6. In both figures, the set $\{0,1\}$ of items activates F_1, but the spatial patterning of STM activities across these items differs. Level F_2 senses this difference and groups the F_1 patterns differently in Figures 5 and 6.

place Figure 6 here

The sensitivity to pattern microstructure is also illustrated by the more demanding examples in Figures 7 and 8. In Figure 7, the set $\{0,1,2\}$ of active items across F_1 most strongly activates a node within the $\{0,1,2\}$ subfield of F_2 (with activity .184), but also weakly activates the $\{0\}$ subfield of F_2 (with activity .004). A different STM pattern over the same set $\{0,1,2\}$ of items is processed by F_2 in Figure 8. Level F_2 groups the F_1 patterns of Figures 7 and 8 differently.

place Figure 7 here

A comparison of Figures 3, 5, and 7 provides an expanded illustration of the sensitivity to multiple spatial scales. A comparison of Figures 3–8 illustrates how the STM activity pattern across F_2 becomes more focussed as increasing information due to an expanded temporal (or spatial) context reduces predictive uncertainty.

place Figure 8 here

Directions of Future Research

The next stage in the development of the adaptive resonance theory can now easily be stated in formal terms: Replace the global choices made by F_2 in the Carpenter and Grossberg chapter with a masking field capable of sensing multiple groupings of an input pattern; extend the $F_1 \leftrightarrow F_2$ hierarchy to multiple coding levels $F_1 \leftrightarrow F_2 \leftrightarrow F_3 \leftrightarrow \ldots \leftrightarrow F_n$; and analyse the recognition invariants that are self-organized by such an expanded attentional-orienting system in biologically important examples. This program, although now easy to state in formal terms, includes as special cases several of the most difficult outstanding problems in cognitive psychology.

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FIGURE CAPTIONS

Figure 1. (a) Selective activation of a masking field: The nodes, or cell populations, in a masking field F_2 are organized so that longer item sequences in F_1, up to some optimal length, activate F_2 list nodes which possess more potent competitive, or masking, properties. Individual items, as well as item groupings, are represented by the list nodes of the masking field. The desired relationship between item field, masking field, and the intervening adaptive filter can be self-organized using simple developmental rules. Cells from an item field F_1 grow randomly to a masking field F_2 along positionally sensitive gradients. The nodes in the masking field grow so that larger item groupings, up to some optimal size, can activate nodes with broader and stronger inhibitory interactions. Thus the $F_1 \rightarrow F_2$ connections and the $F_2 \leftrightarrow F_2$ interactions exhibit properties of self-similarity. (b) The interactions within a masking field F_2 include positive feedback from a node to itself and negative feedback from a node to its neighbors. Long term memory (LTM) traces at the ends of $F_1 \rightarrow F_2$ pathways (designated by hemidisks) adaptively tune the filter defined by these pathways to amplify the F_2 reaction to item groupings which have previously succeeded in activating their target F_2 nodes.

Figure 2. Two types of masking field sensitivity: (a) Masking field F_2 can automatically rescale its sensitivity to react differentially to activity patterns that activate variable numbers of F_1 cells. It hereby acts like a "multiple spatial frequency filter." (b) A masking field can differentially react to different F_1 activity patterns that activate the same set of F_1 cells. By (a) and (b), F_2 acts like a spatial pattern discriminator that can compensate for changes in overall spatial scale without losing its sensitivity to pattern changes at the finest spatial scale.

Figure 3. List coding of a single item: Network F_1 encodes in short term memory (STM) a spatial pattern of activation over item representations. In this figure, the single item $\{0\}$ is activated. Network F_2 encodes in STM the pattern of sublist chunks that are

activated by F_1. The first three rows depict the inputs from F_1 and F_2. They are broadly distributed across F_2. The List Code in STM depicts the STM response to these inputs. The correct $\{0\}$ is preferred in STM, but predictive list codes which include $\{0\}$ as a part are also activated with lesser STM weights. The prediction gets less activation if $\{0\}$ forms a smaller part of it.

Figure 4. List coding of a single item: The correct list code $\{1\}$ in F_2 in response to item $\{1\}$ at F_1 is preferred in STM, but the predictive list codes which include $\{1\}$ as a part are also activated with lesser STM weights.

Figure 5. List coding of an STM primacy gradient across two items: A primacy gradient in STM across two items of F_1 generates an even broader input pattern to F_2. A list code of type $\{0,1\}$ is maximally activated, but part codes $\{0\}$ and predicted codes which include $\{0,1\}$ as a part are also activated with lesser STM weights. Comparison with Figure 3 shows that F_2 can update its internal representation of input configurations in a context-sensitive way.

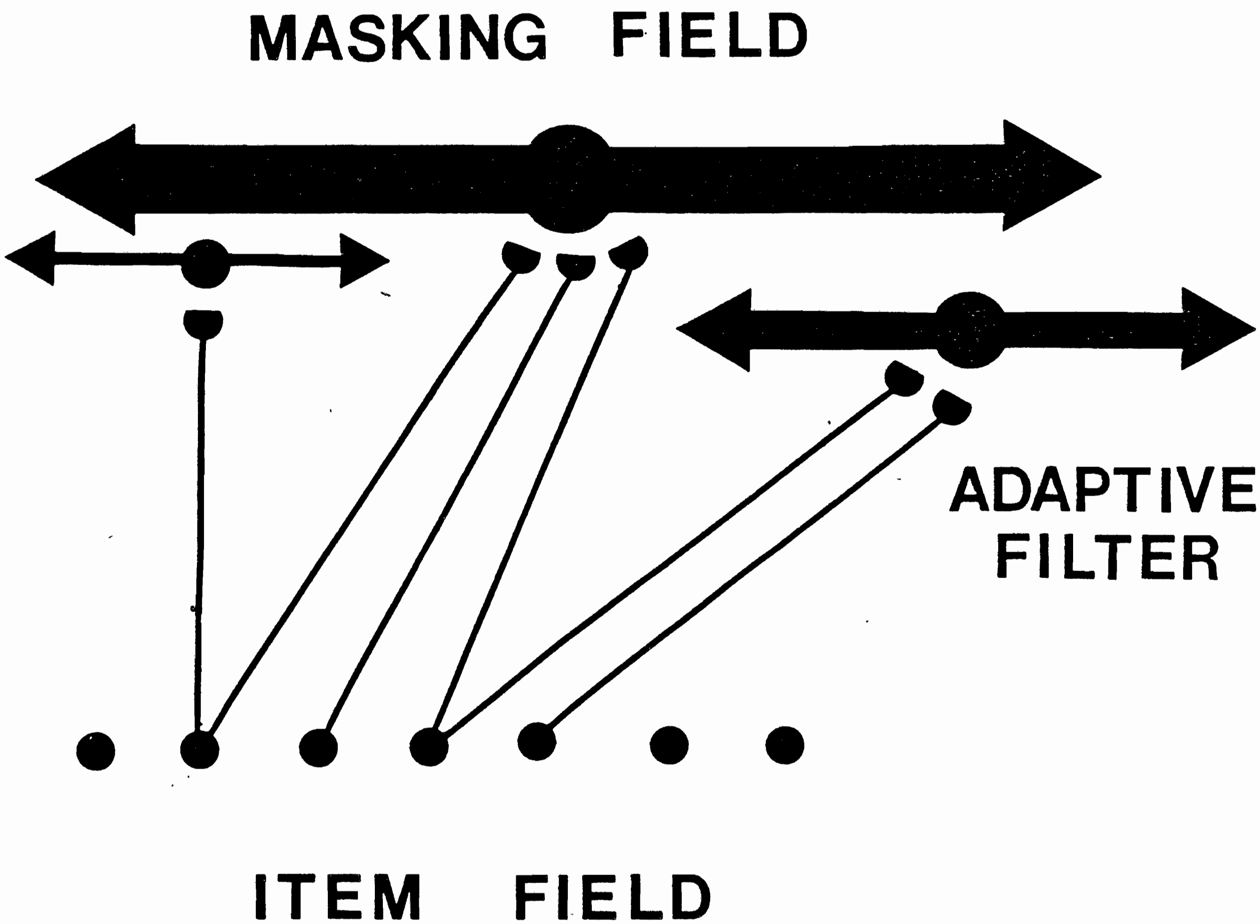
Figure 6. List coding of an STM recency gradient across two items: A recency gradient in STM occurs across the same two items of F_2, rather than a primacy gradient. A *different* $\{0,1\}$ list code population is preferred, as are different part and prediction codes. Thus F_2 can distinguish different spatial patternings among the same items.

Figure 7. List coding of an STM primacy gradient across three items: In this figure, a primacy gradient in STM occurs across three items of F_1. The input pattern to F_2 is even broader than before. However, the STM response of F_2 retains its selectivity. The list code in STM strongly activates an appropriate $\{0,1,2\}$ list code. Part groupings are suppressed due to the high level of predictiveness in this masking field, since each F_2 node receives input pathways from at most three F_1 item nodes. Comparison of Figures 3, 5, and 7 shows that as the item code across F_1 becomes more constraining, the list code representation becomes less distributed across F_2.

Figure 8. List coding of an STM recency gradient across three items: In this figure, a different spatial pattern across the same three items in F_1 generates a different selective STM response among the $\{0,1,2\}$ nodes at F_2, thereby illustrating F_2's sensitivity to F_1 pattern microstructure.

AUTHOR INDEX

SUBJECT INDEX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ADAPTIVE
FILTER
ITEM FIELD

Figure 1b

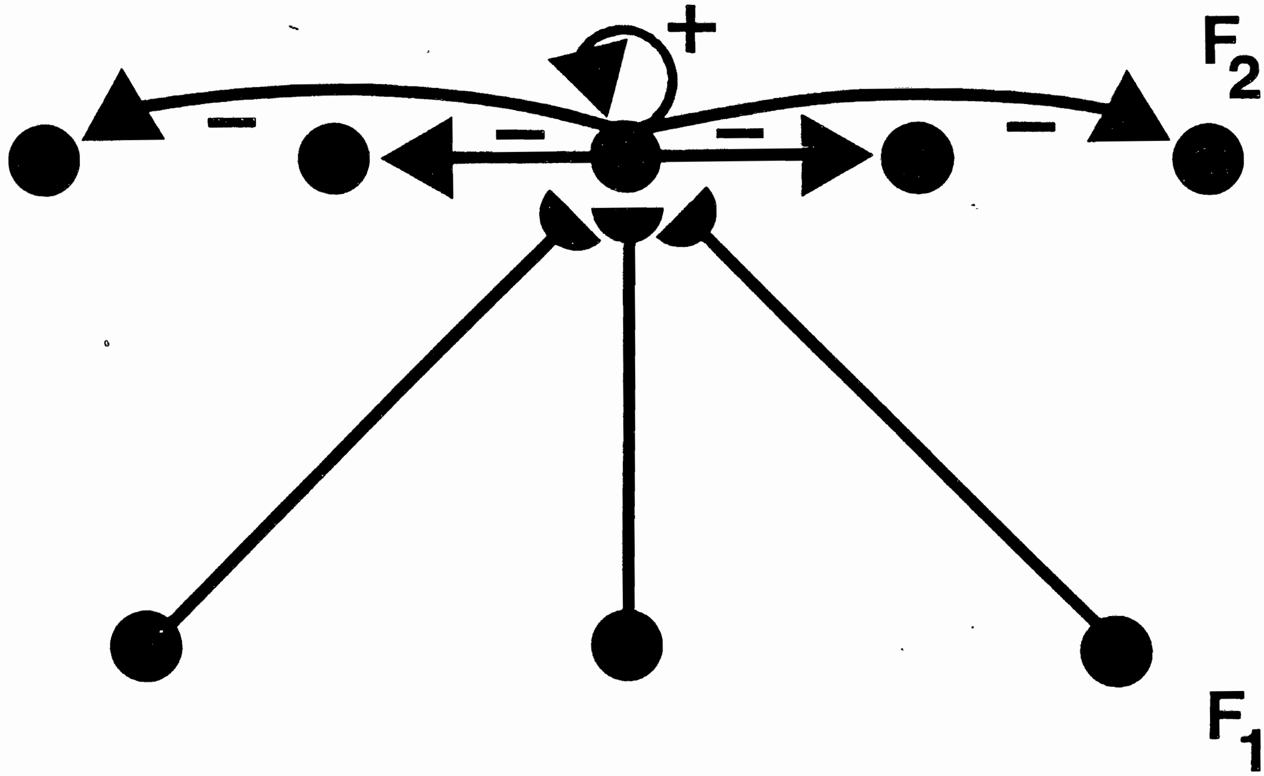


Figure 2

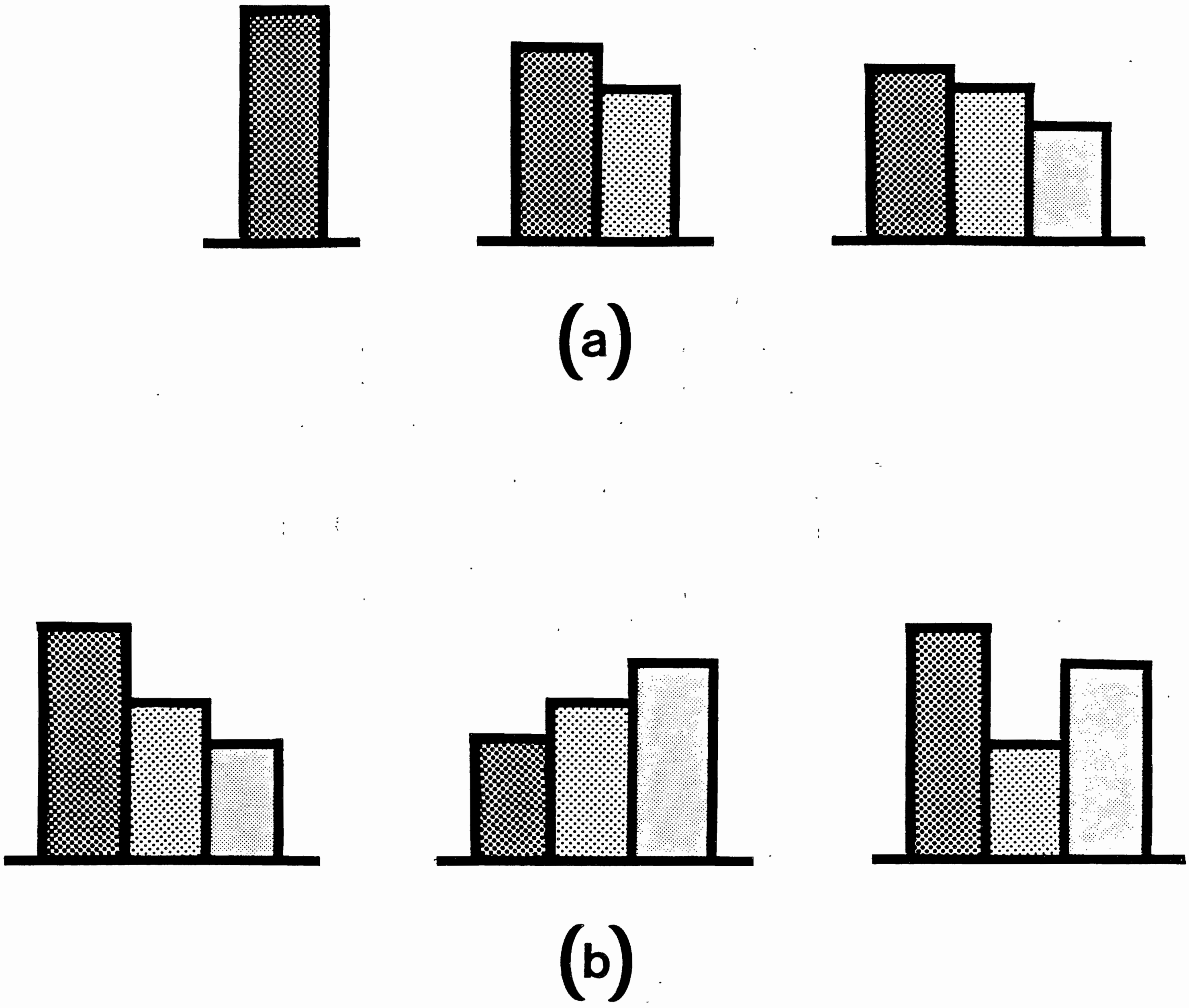
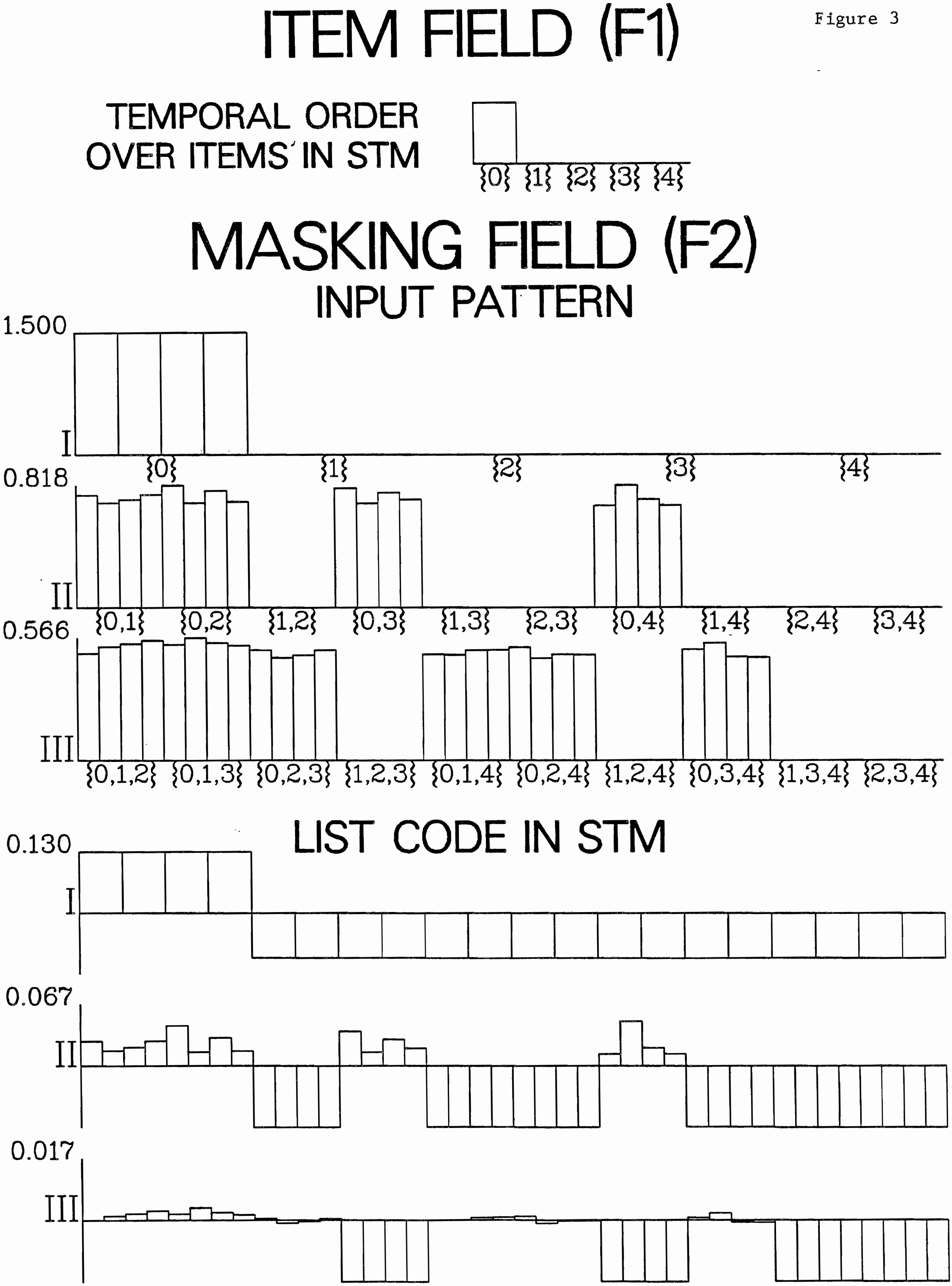
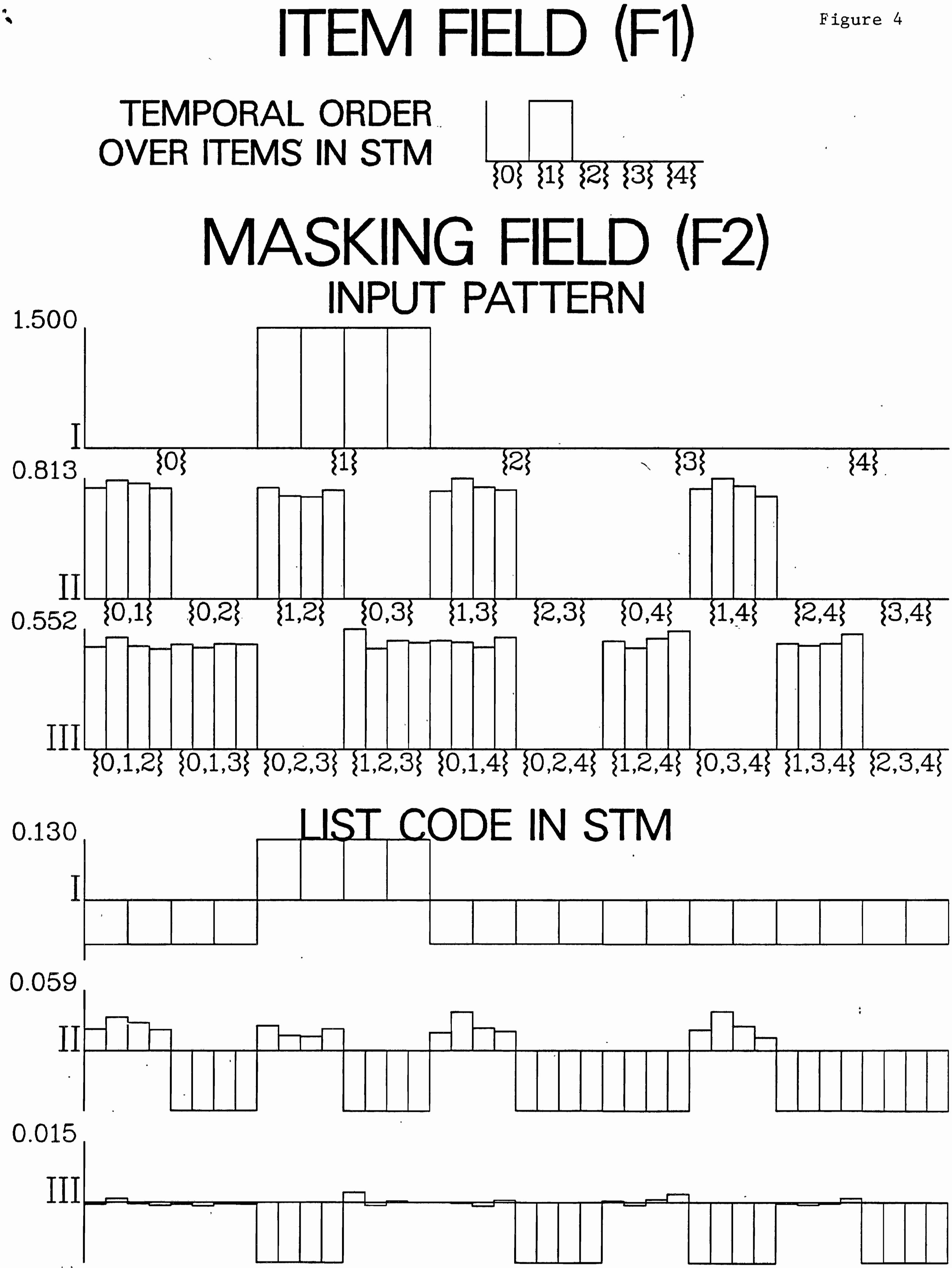


Figure 3



ITEM FIELD (F1)
TEMPORAL ORDER
OVER ITEMS IN STM
{0} {1} {2} {3} {4}
MASKING FIELD (F2)
INPUT PATTERN
1.500
I
{0} {1} {2} {3} {4}
0.818
II
{0,1} {0,2} {1,2} {0,3} {1,3} {2,3} {0,4} {1,4} {2,4} {3,4}
0.566
III
{0,1,2} {0,1,3} {0,2,3} {1,2,3} {0,1,4} {0,2,4} {1,2,4} {0,3,4} {1,3,4} {2,3,4}
LIST CODE IN STM
0.130
I
0.067
II
0.017
III

Figure 4



ITEM FIELD (F1)
TEMPORAL ORDER
OVER ITEMS IN STM
{0} {1} {2} {3} {4}
MASKING FIELD (F2)
INPUT PATTERN
1.500
I
{0} {1} {2} {3} {4}
0.813
II
{0,1} {0,2} {1,2} {0,3} {1,3} {2,3} {0,4} {1,4} {2,4} {3,4}
0.552
III
{0,1,2} {0,1,3} {0,2,3} {1,2,3} {0,1,4} {0,2,4} {1,2,4} {0,3,4} {1,3,4} {2,3,4}
LIST CODE IN STM
0.130
I
0.059
II
0.015
III

Figure 5

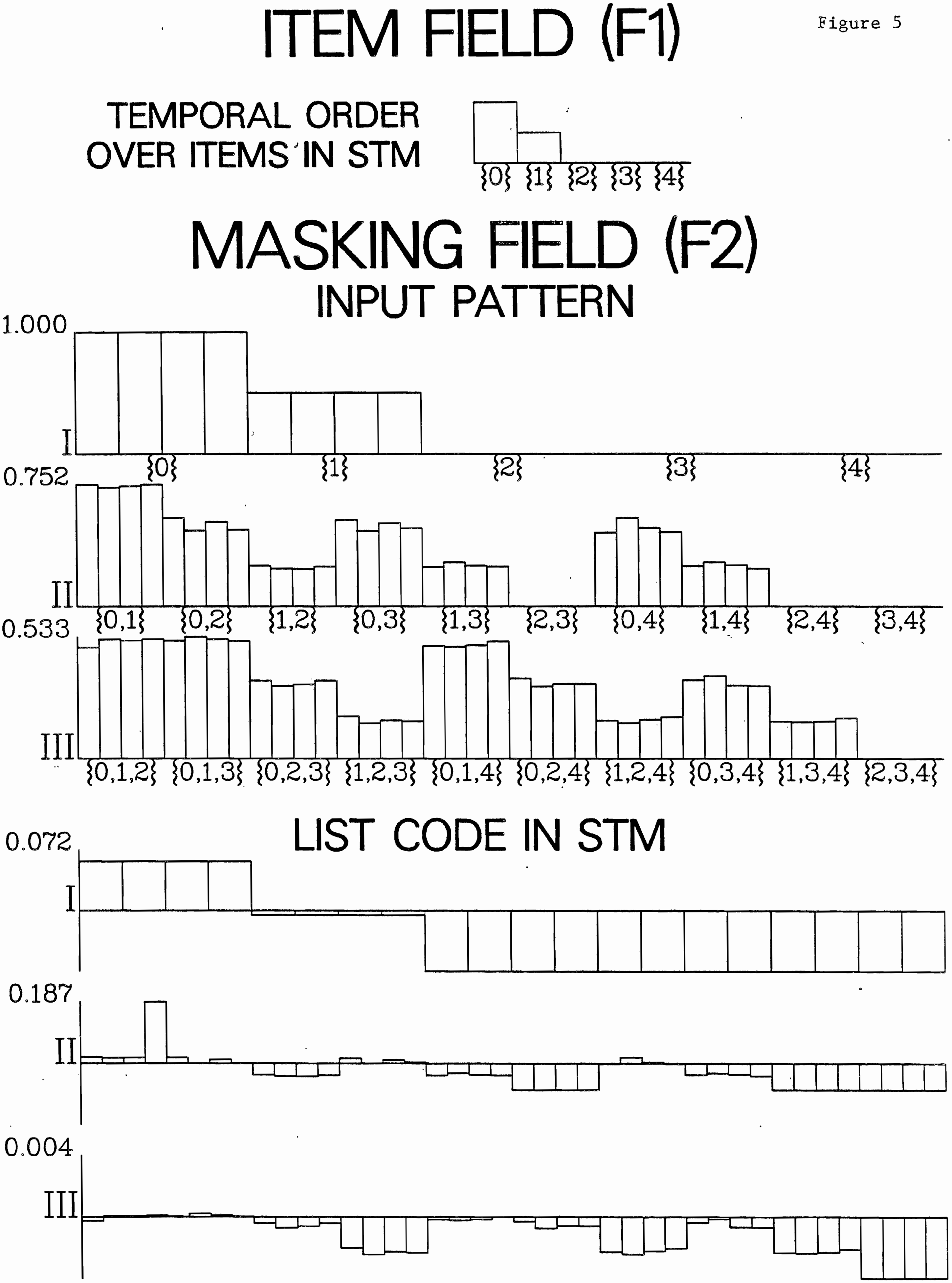
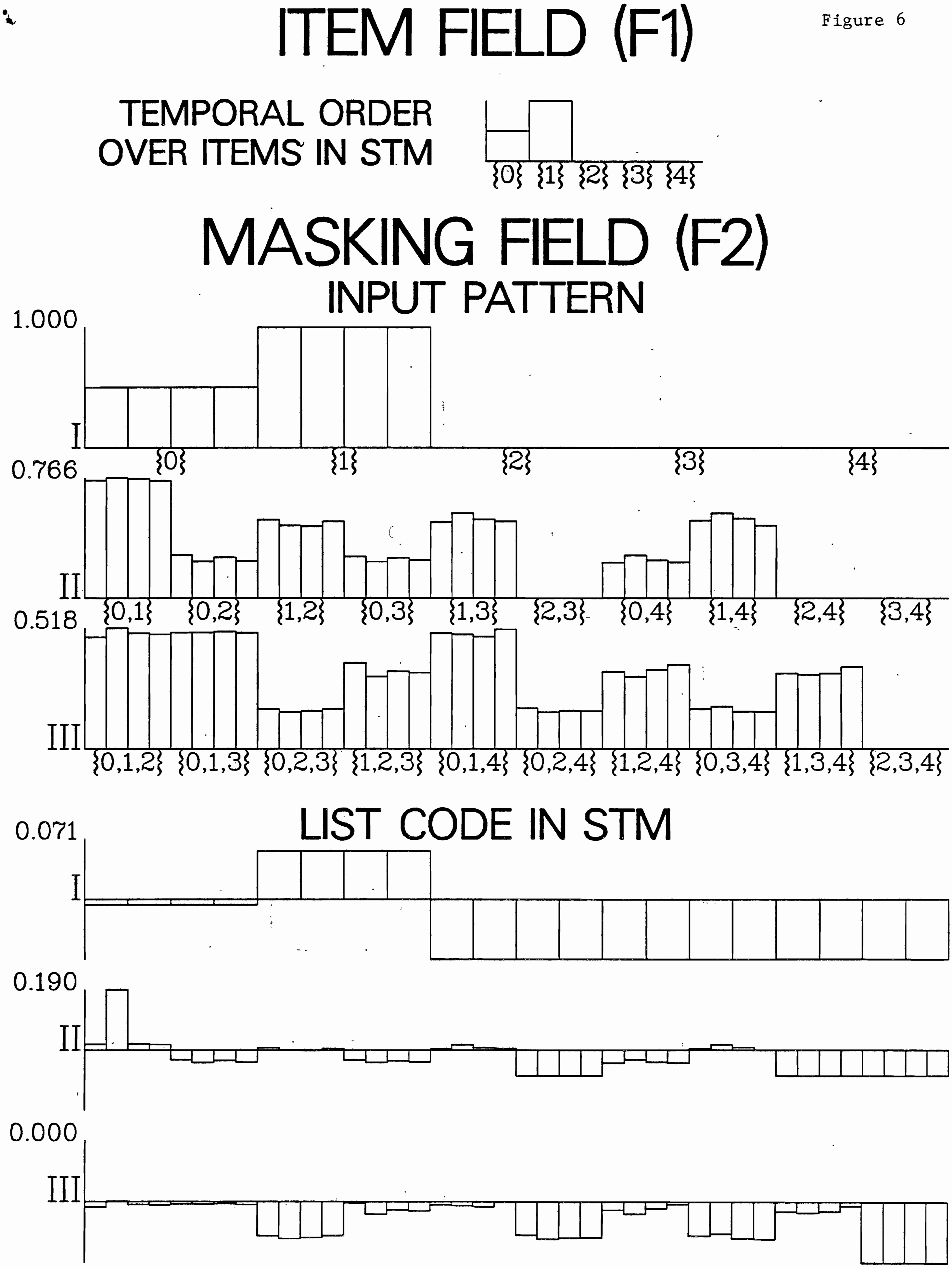
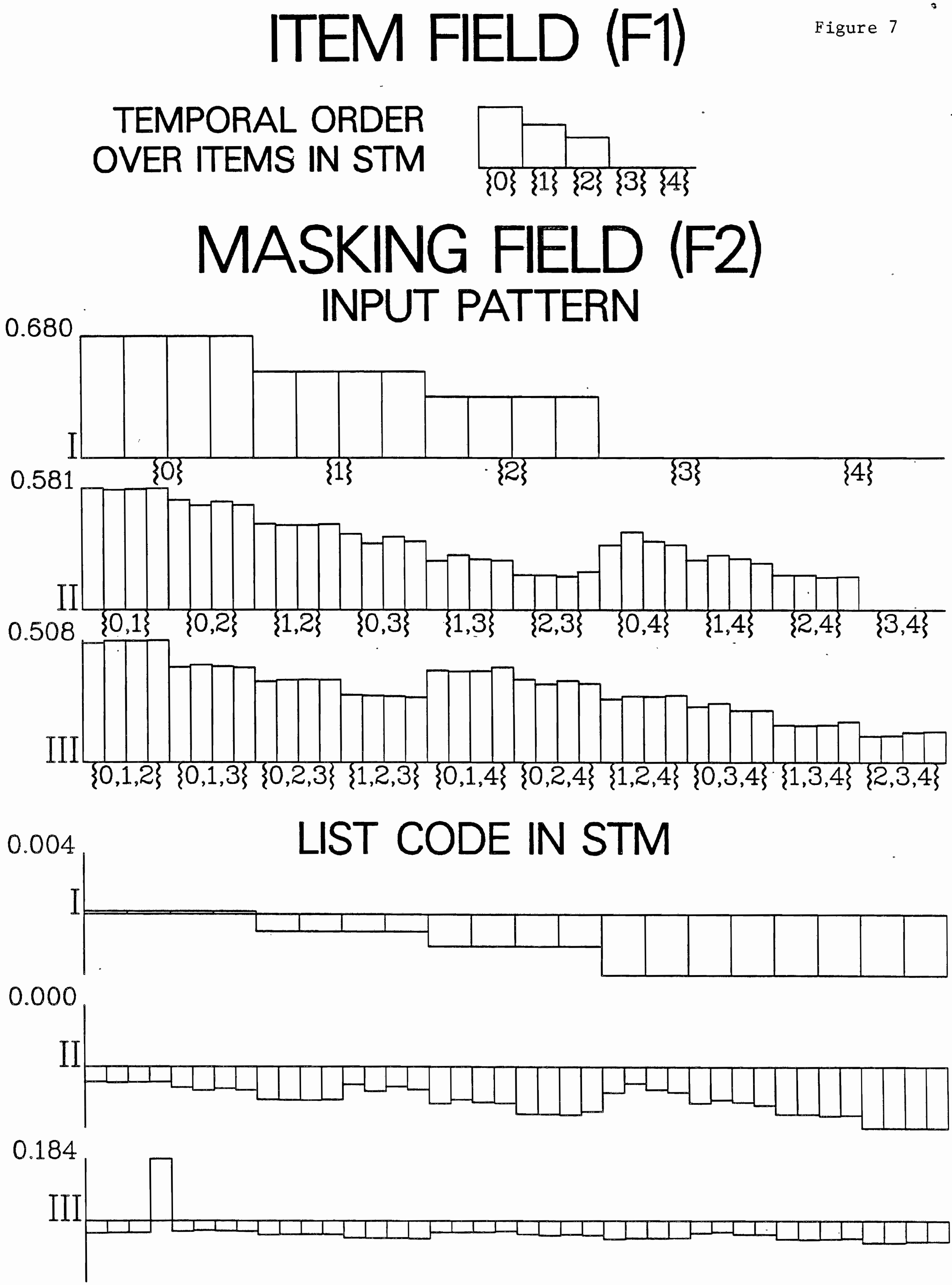

ITEM FIELD (F1)
TEMPORAL ORDER
OVER ITEMS IN STM
{0} {1} {2} {3} {4}
MASKING FIELD (F2)
INPUT PATTERN
1.000
I
{0} {1} {2} {3} {4}
0.752
II
{0,1} {0,2} {1,2} {0,3} {1,3} {2,3} {0,4} {1,4} {2,4} {3,4}
0.533
III
{0,1,2} {0,1,3} {0,2,3} {1,2,3} {0,1,4} {0,2,4} {1,2,4} {0,3,4} {1,3,4} {2,3,4}
LIST CODE IN STM
0.072
I
0.187
II
0.004
III

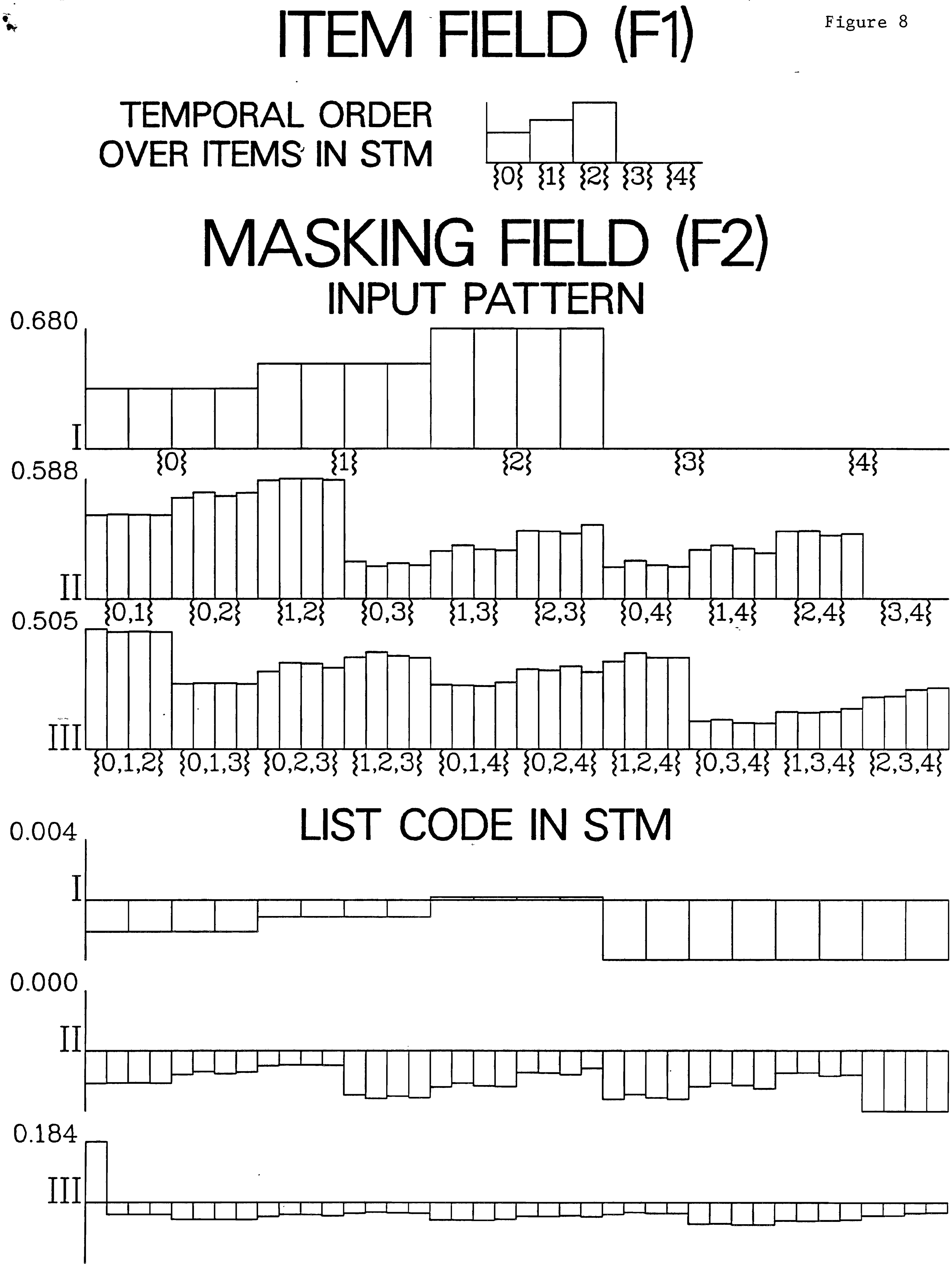
Figure 6



ITEM FIELD (F1)
TEMPORAL ORDER
OVER ITEMS IN STM
{0} {1} {2} {3} {4}
MASKING FIELD (F2)
INPUT PATTERN
1.000
I
{0} {1} {2} {3} {4}
0.766
II
{0,1} {0,2} {1,2} {0,3} {1,3} {2,3} {0,4} {1,4} {2,4} {3,4}
0.518
III
{0,1,2} {0,1,3} {0,2,3} {1,2,3} {0,1,4} {0,2,4} {1,2,4} {0,3,4} {1,3,4} {2,3,4}
LIST CODE IN STM
0.071
I
0.190
II
0.000
III

Figure 7


ITEM FIELD (F1)
TEMPORAL ORDER OVER ITEMS IN STM
{0} {1} {2} {3} {4}
MASKING FIELD (F2)
INPUT PATTERN
0.680
I
{0} {1} {2} {3} {4}
0.581
II
{0,1} {0,2} {1,2} {0,3} {1,3} {2,3} {0,4} {1,4} {2,4} {3,4}
0.508
III
{0,1,2} {0,1,3} {0,2,3} {1,2,3} {0,1,4} {0,2,4} {1,2,4} {0,3,4} {1,3,4} {2,3,4}
LIST CODE IN STM
0.004
I
0.000
II
0.184
III


ITEM FIELD (F1)
TEMPORAL ORDER OVER ITEMS IN STM
{0} {1} {2} {3} {4}
MASKING FIELD (F2)
INPUT PATTERN
0.680
I
{0} {1} {2} {3} {4}
0.588
II
{0,1} {0,2} {1,2} {0,3} {1,3} {2,3} {0,4} {1,4} {2,4} {3,4}
0.505
III
{0,1,2} {0,1,3} {0,2,3} {1,2,3} {0,1,4} {0,2,4} {1,2,4} {0,3,4} {1,3,4} {2,3,4}
LIST CODE IN STM
0.004
I
0.000
II
0.184
III