Problem Decomposition on Restructuring Shapes in terms of Emergent Subshapes

submitted to *CAAD Futures '95*

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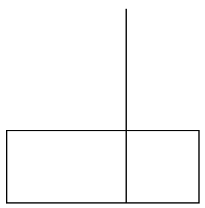
Generalizing Searchlight Scopes for More Difficult Problems

The above simulations are all based upon square scopes for searchlight attention. However, as mentioned in the section on Searchlight attention processing, although there is no doubt that human being's scopes of searchlight attention can be circular or square, there is no scientific evidence that proves this point. These square searchlight scopes, such as the 4-by-4, 5-by-5, and 6-by-6 scopes used in the above simulations, work perfectly with the two overlapping primary squares because the boundaries of the expected emergent subshapes—two larger squares, two smaller squares, and two L-shape polygons—are all square. This unintended correspondence simplifies the situations and thus makes the proposed method (Figure 4-31) too limited to work with other shapes which are normal in design. This section explores the networks' ability to encode a primary shape whose subshapes' boundaries are no longer square. Another important issue here is how to deal with line drawings or a primary shape consisting of single lines.



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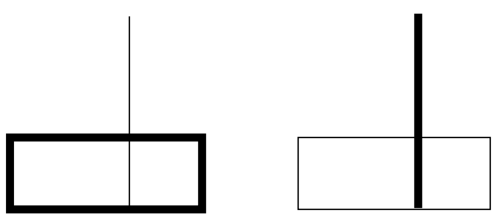

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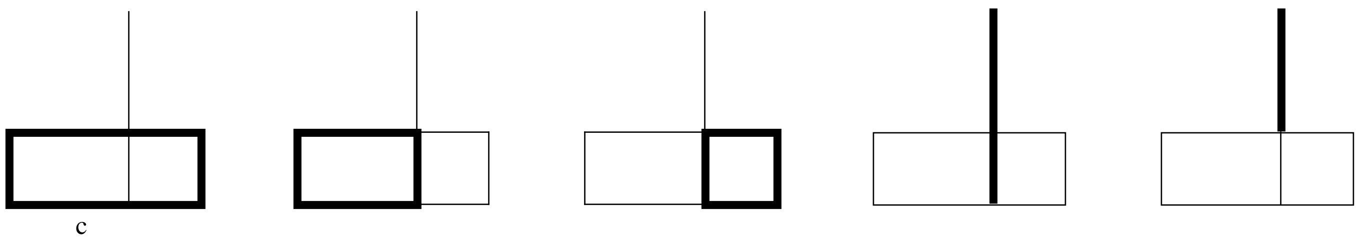


Figure 4-40: A shape (a) consisting of a rectangle and a line (b) and some of its explicit emergent subshapes (c).

The primary shape used here is shown in Figure 4-40a: it can be drawn as a rectangle and a line. Consider a simpler case of shape emergence, namely encoding explicit subshapes only. The explicit emergent subshapes should contain not only the two primary objects in Figure 4-40b but also another smaller rectangle, a square, and another two shorter lines on top of the original one as illustrated in Figure 4-40c. Compared to the problem of two overlapping squares, it is more difficult to restructure this primary shape: not only are there more explicit emergent subshapes to recognize but the subshapes have a variety of boundaries including 1-by-3, 1-by-5, and 1-by-7 for the lines and 3-by-3, 3-by-5, and 3-by-7 for the squares and rectangles.

The connectionist networks must learn these subshapes during the *training* procedure in order to restructure the above primary shape in terms of its subshapes during the *testing* procedure. In other words, in an attempt to "increase" the network's ability to recognize more shapes, it has to work "harder" to learn in the first place. In the following simulations, six shapes, which belong to the explicit subshapes of the updated primary shape (Figure 4-41), are added into the original set of training patterns (Figure 4-9). Note that the total number of training patterns from now on is 31.

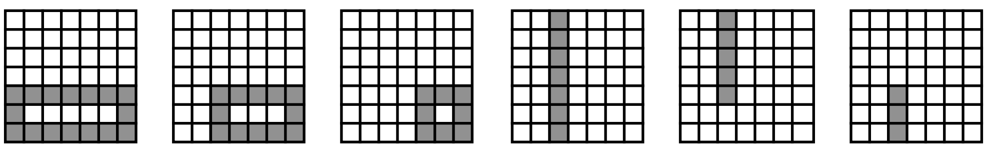
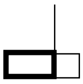
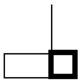
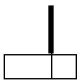


Figure 4-41: Additional training patterns to the original training set as shown in Figure 4-9.

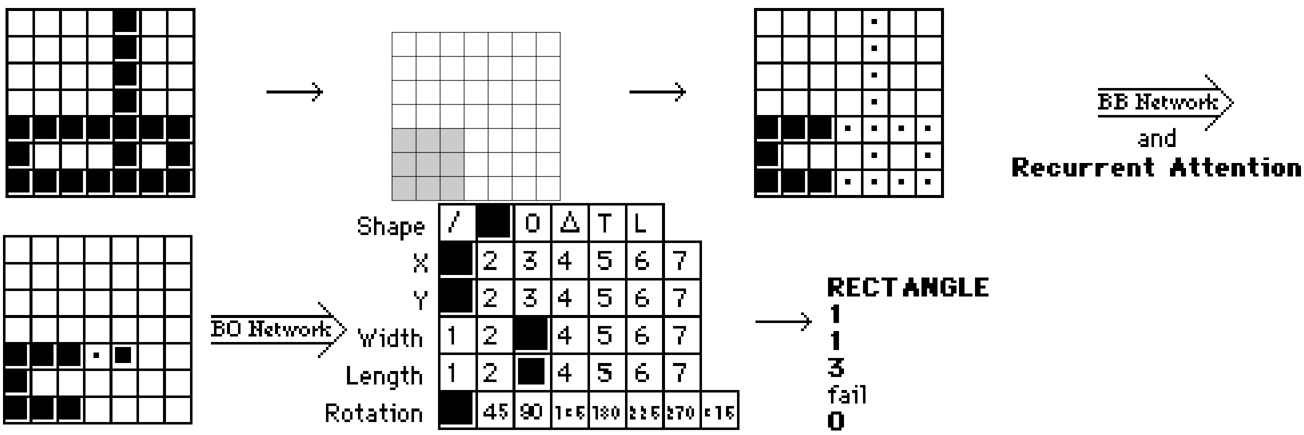
To work on this "wicked" problem of emergent shapes (Figure 4-40), we first utilized the original procedure with square searchlight scopes as shown in Figure 4-31. A simulation was taken based on a specific variable setting: TRA is set at 0.95, the outside activation strength at 0.13, and the number of recurrent cycles at 1. Note that a high TRA of 0.95 is used here to eliminate all possible distracted images as stated previously. The simulation result is illustrated in Figure 4-42: after moving the 3-by-3, 4-by-4 and 5-by-5 searchlight all over the receptive field, the networks only encode three subshapes as follows:

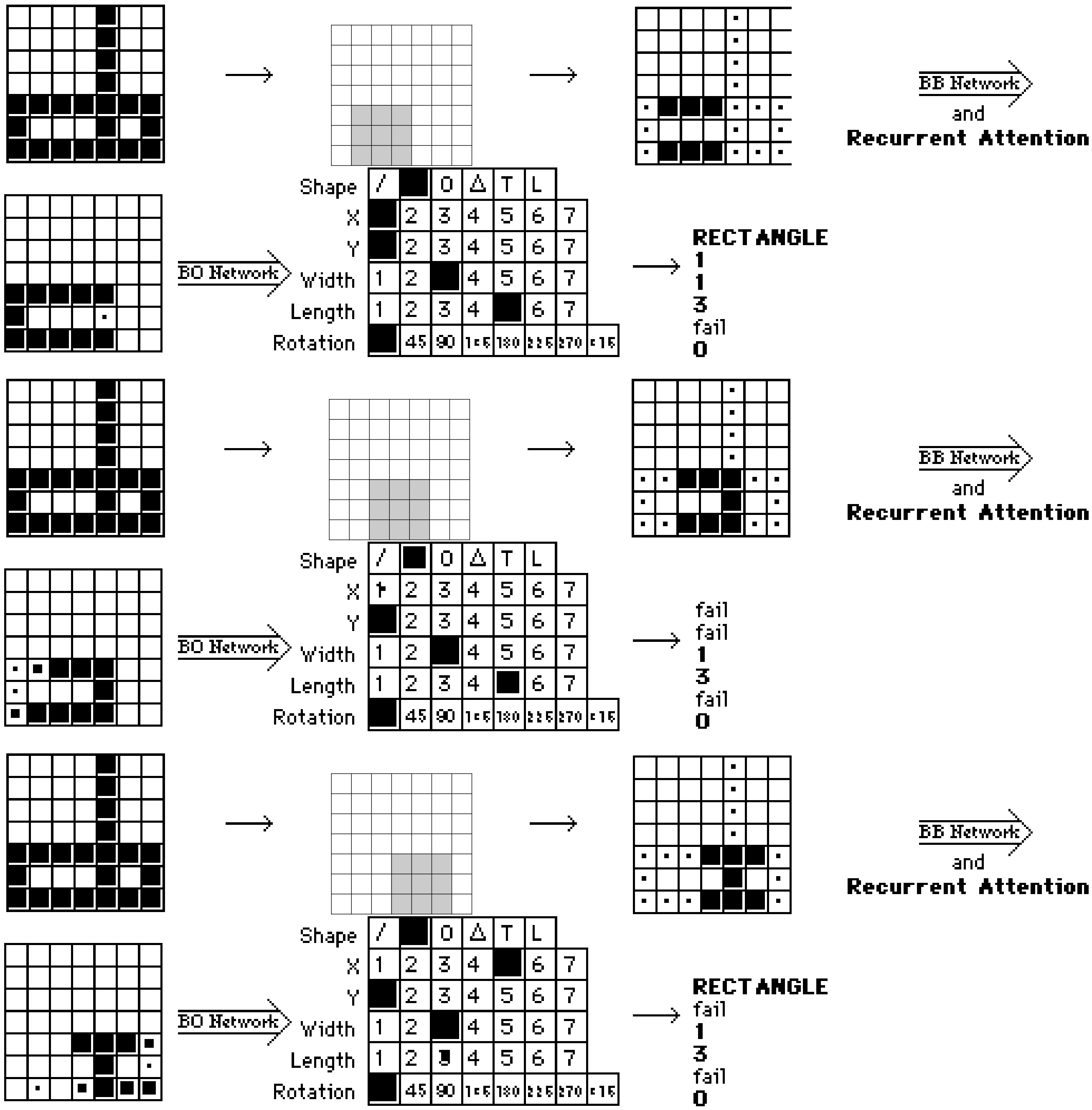

(rectangle 1 1 3 5 0)


(square 5 1 3 3 0)


(line 5 3 5 1 0)

The cause of this poor performance of the networks is obvious. The square scopes of searchlight attention are either too small or too big: when a side of the scope fits the smaller side of an expected object, the searchlight scope is too small to cover the entire shape to pay full attention on it; when the scope is big enough to cover the entire object, it very possibly includes other objects inside. Because of the fixed square proportion of searchlight scopes, unfortunately, there is no way to improve this inadequacy of the connectionist networks. An efficient method that may overcome this limitation is to associate the original mechanism of searchlight attention with other scopes in non-square proportions in addition to original square ones so that scopes in different proportions can fit different subshapes. Again, although there is no psychological data about the searchlight scope's proportion on visual selective attention, it is theoretically plausible and computationally feasible to implement this unproved concept in order to increase the ability of CAAD systems. Of course, to verify the use of non-square scopes for searchlight attention will require other in-depth investigations in both experimental psychology and neuroscience.

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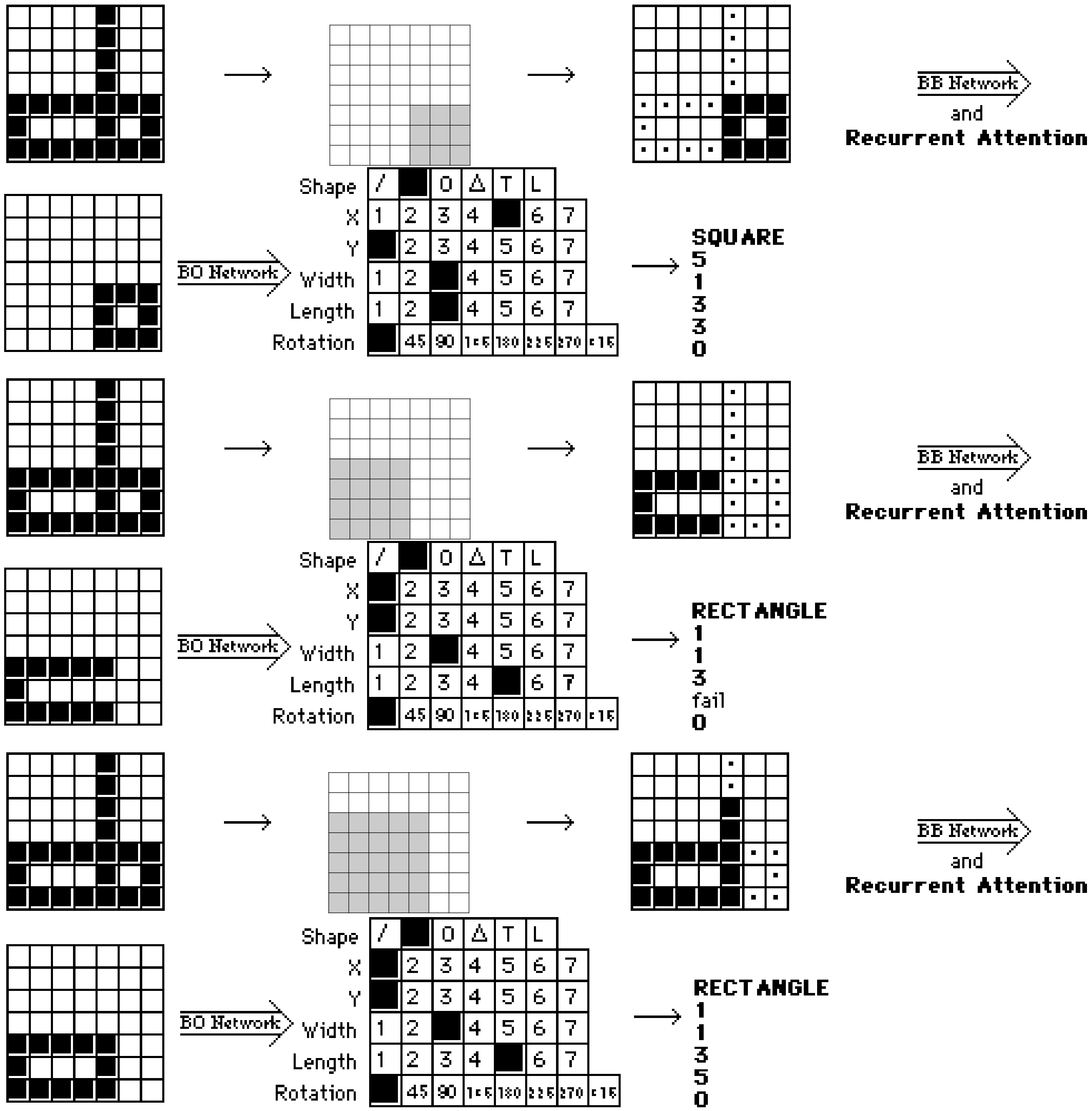
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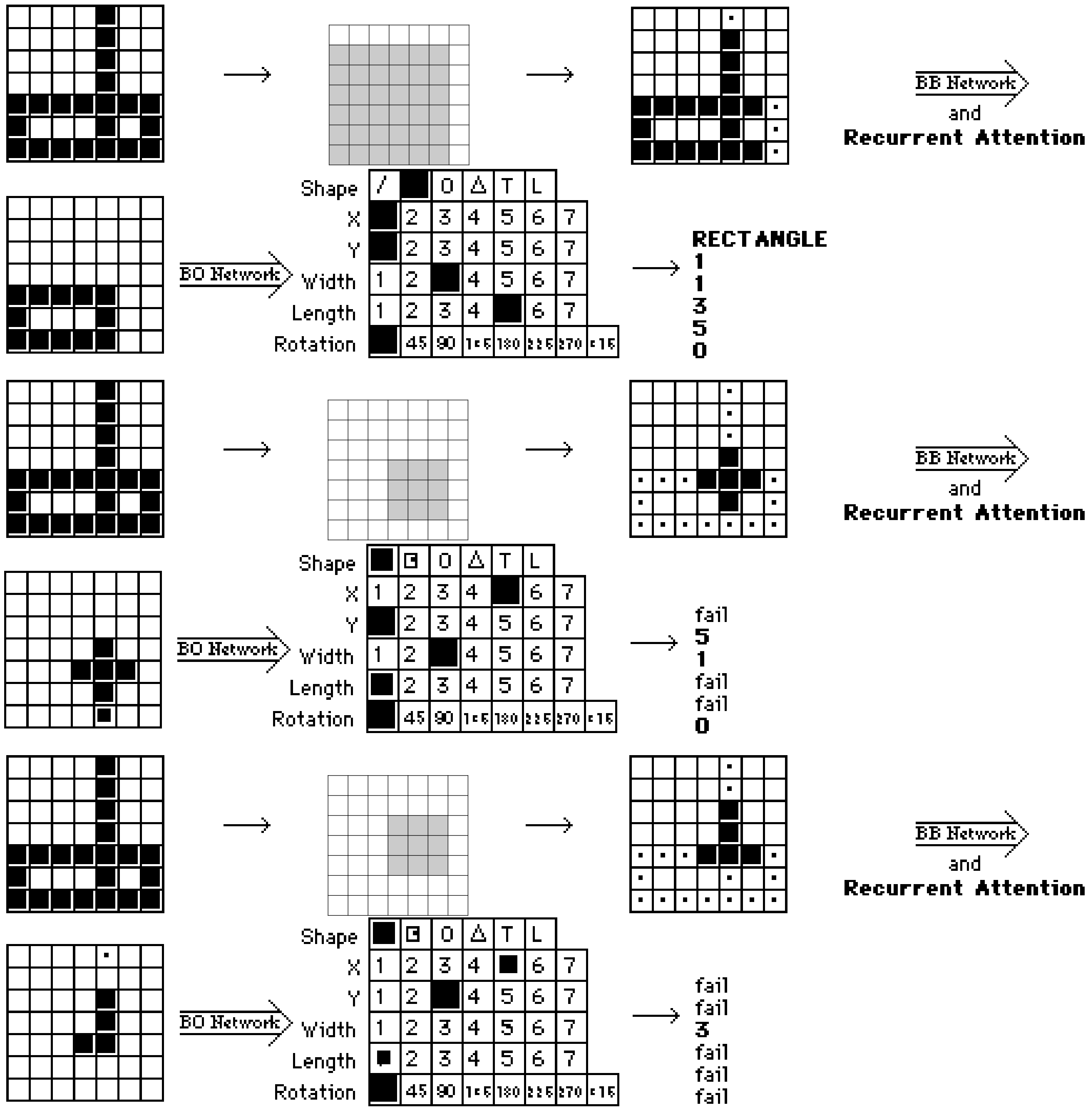


Figure 4-42: Simulation result of encoding the more difficult primary shape using the networks with both searchlight and recurrent attention (See Figure 4-28 for note).

One fundamental approach to solving an ill-defined problem in AI and cognitive psychology is to decompose a problem into subproblems and, following the same thought, to decompose a more difficult problem into more subproblems (Simon 1981; Akin 1986). By analogy, to successfully encounter the above shape restructuring problem which is more difficult, decomposing the problem into more subproblems by applying more searchlight scopes in a variety of proportions onto the receptive field. By doing so, the problem of encoding the primary shape is then decomposed into 419 subproblems in terms of moving 34 possible scopes of searchlight attention (Figure 4-43) all over around the receptive field.

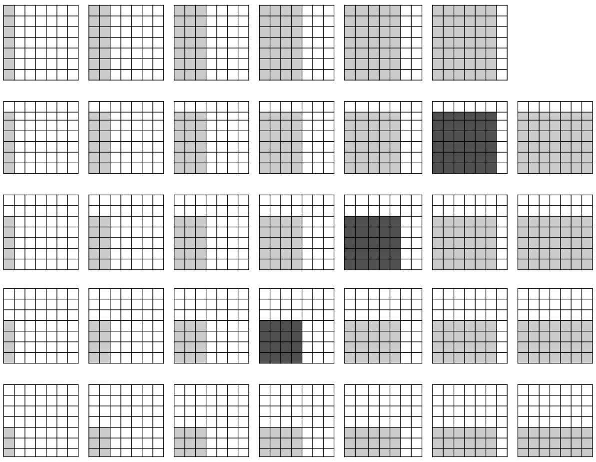
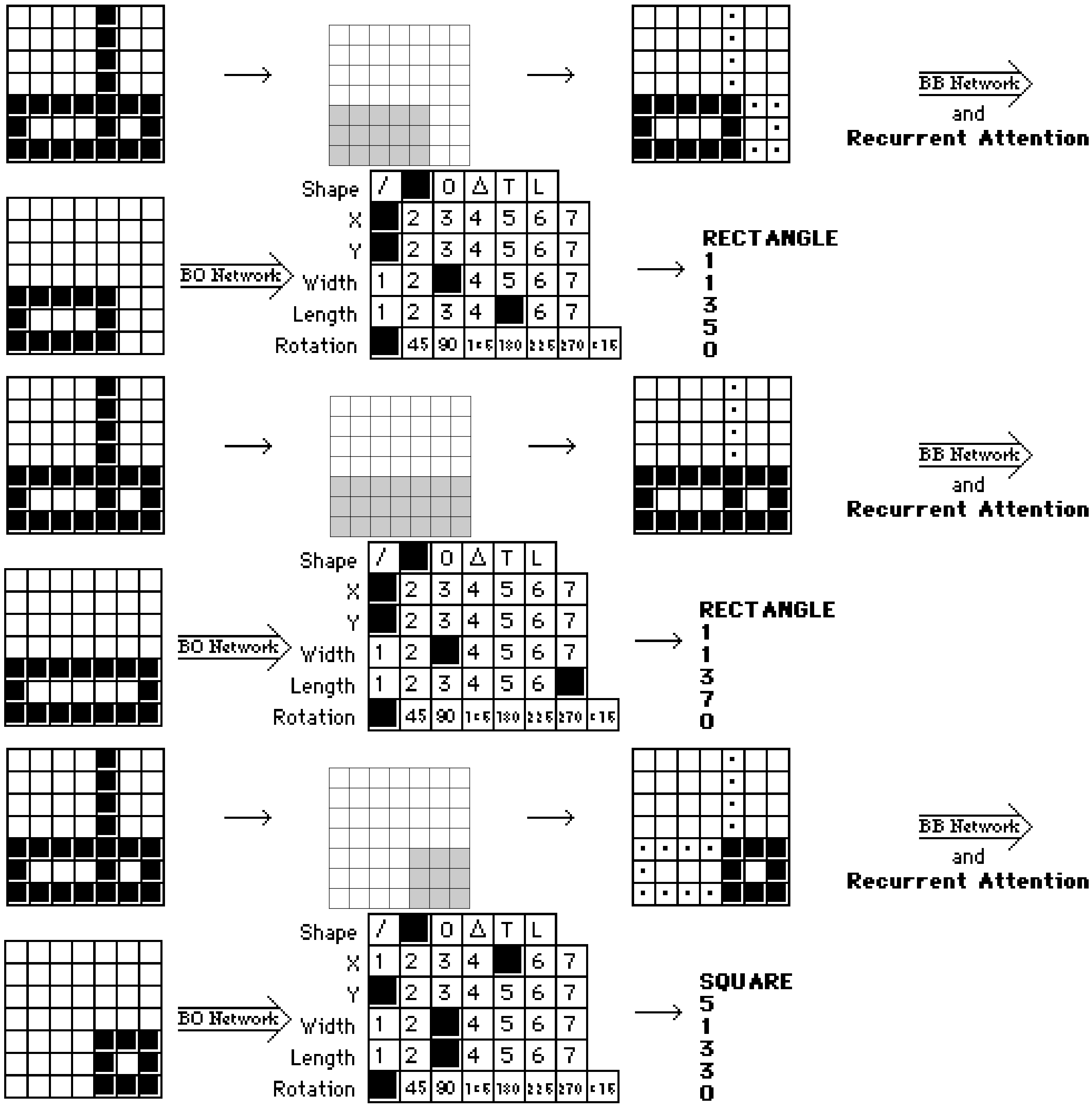


Figure 4-43: Some possible scopes for searchlight attention. (The three square scopes with heavier gray patterns are the ones used in preceding sections).

In one sense, to decompose a receptive field into hundreds of visual portions to be recognized is slightly similar to the template-matching model for pattern recognition in human vision (Anderson 1990). However, the two processes are fundamentally distinct: template-matching relies upon the exact number of inner templates for testing patterns but the proposed hundreds of searchlight scopes can handle much more than hundreds of testing shapes, in fact thousands or even millions of them. However, to some extent, template-matching can be seen as an extreme case of searchlight attention. Consider why we need so many scopes and possible locations here. According to the typical *binding problem* in connectionism under the situation of processing multiple objects simultaneously (Figure 4-10 and 4-12), the only way to overcome this "information limit" (Minsky 1963) is to try hard to deal with one object at a time, using external aids. For the simpler problem of two overlapping squares, three kinds of square scopes enable the networks to deal with one shape at a time; the second primary shape, which is more difficult, needs much more external aid to achieve the same goal. In sum, no matter how many searchlight scopes and locations are needed to decompose the primary shapes, there is a common goal—to process one shape at a time in order to overcome the spontaneous information limit.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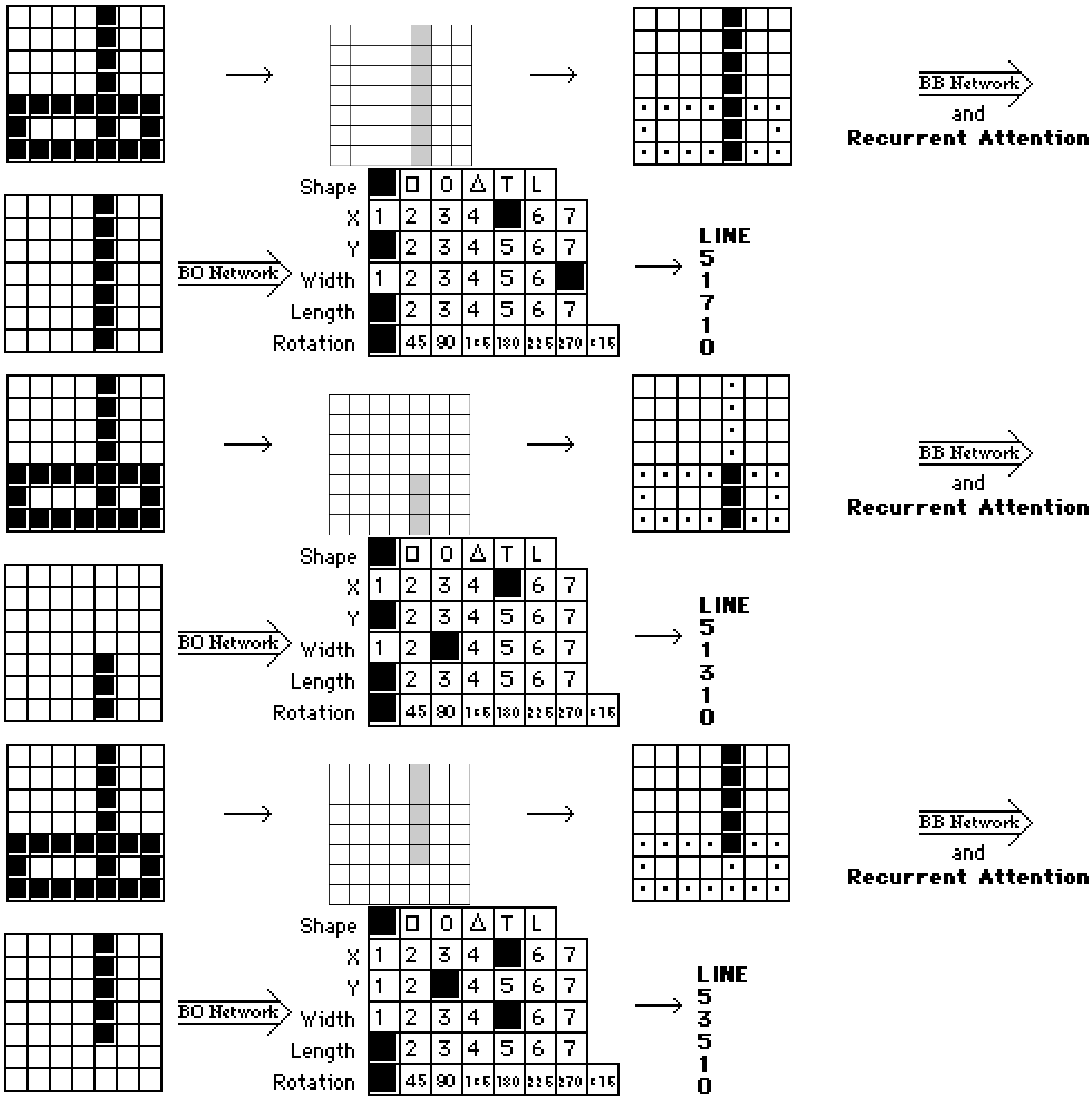
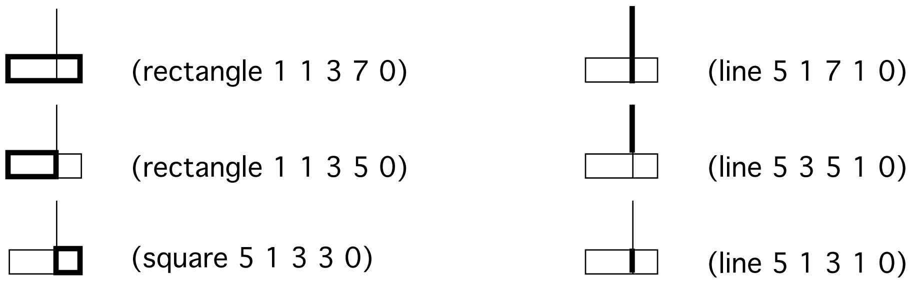


Figure 4-44: Simulation result of encoding the more difficult primary shape using the networks with additional non-square searchlight scopes. (See Figure 4-28 for note.)

The variable setting of the current simulation that implements the above "possible searchlight scopes" idea is the same as that of the last simulation in order to prevent any distracted images from occurring. The simulation results are shown in Figure 4-44. By means of the 420 procedures that pay searchlight and recurrent attention to different portions of the primary shape, the networks can find the six expected emergent subshapes as follows:



The result indicates that it is computationally valid and valuable to use non-square scopes for searchlight attention to encounter restructuring shape problems, although the psychological and neuroscientific basis for implementing the concept needs more investigation. This study explores a way to deal with both more difficult shapes and line drawings that are practical and common. Lines are elementary and thus important in the real world. However, in most conditions, any closed shape is always dominant over a line as a line is dominant over a point by analogy with the common reading phenomenon that a word is always dominant over a letter (Figure 4-45). Therefore an alliterative method to deal with line drawings should be to split the restructuring shape problem into two hierarchies (Figure 4-46): first, to recognize closed shapes, and then to recognize lines by using the subshapes acquired from the first hierarchical procedure as testing inputs in the second hierarchy here. This theoretically feasible idea to deal with line drawings is an important future direction of investigation.

Figure 4-45: Examples of pattern domination: a word "WORD" is dominant over the letters "W," "O," "R," and "D" and a square is dominant over the four lines.

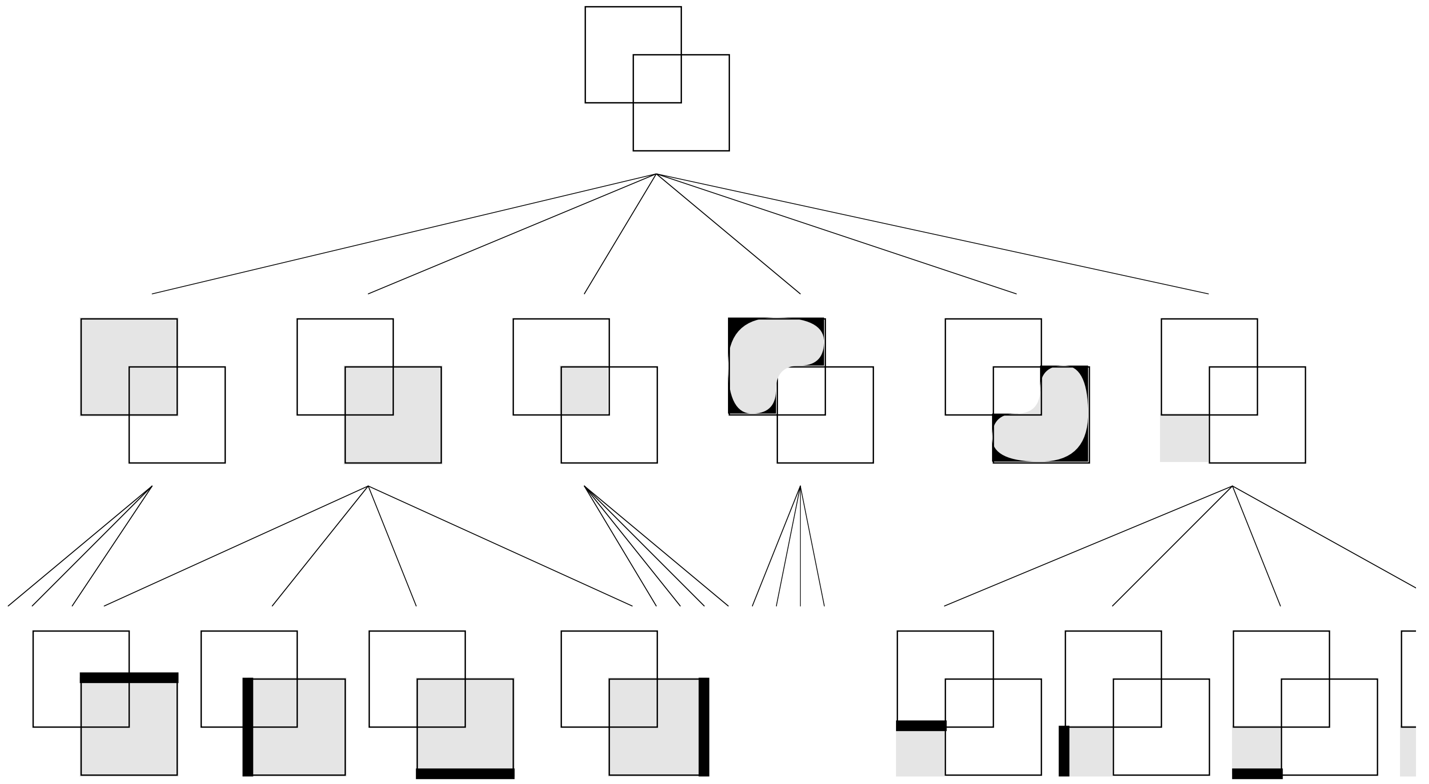


Figure 4-46: Two-hierarchy procedure for restructuring shapes including line recognition.

Although the two-hierarchy procedure for restructuring shapes including line recognition is recommended for computational efficiency and psychological accordance as mentioned above, the simulation in this section can still handle lines well. This illustrates one of the characteristics of the proposed procedure of connectionist networks with visual attention—adjustability meaning that the procedure is adjustable to successfully process simpler and more difficult shapes, and even closed shapes and singular lines. Following the same idea, it is possible to recognize points in shapes by adjusting the searchlight scope to include a 1-by-1 aperture if and only if point recognition is one of the goals and the expected points have been trained in the first place. In conclusion, depending upon the computational flexibility, the mechanism of searchlight attention provides the connectionist networks with the potential to address practical problems of shapes including different scales, different proportions and even simply line drawings.

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