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DEVELOPING A NEURAL NETWORK AS A NOISE FILTER (UNCLASSIFIED)

RAMON RIVERO
U.S. ARMY ARMAMENT,
MUNITIONS AND CHEMICAL COMMAND
ROCK ISLAND, IL 61299-6000

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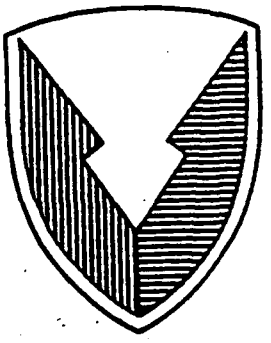

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This study uses the neural network simulator called NETS to determine if neural networks could perform a non-linear filtering operation to remove noise from two-dimensional (2-D) data and produce a noise-free image. Application is geared toward the development and performance of neural network filters, including the development of an optional neural network architecture and the use of criteria in determining how accurate the net filtered noise to produce a noise-free image.

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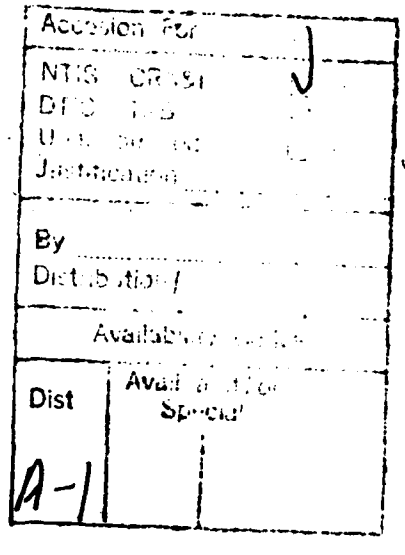
DISCLAIMER

The findings in this report are not to be construed as an official Department of the Army position unless so designated by other authorized documents. Please reference NET'S Users' Guide for more details on how to operate the software.



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EXECUTIVE SUMMARY

The purpose of this study was to determine if neural networks could perform a non-linear filtering operation to remove noise from two-dimensional (2-D) data and produce a noise-free image using NETS, an interpretive neural network simulator.

The majority of this study concentrates on the development and performance of neural network filters. The study begins with developing architectures in a straight vector format using a training set of one sample. The report progresses to architectures arranged in a matrix format using a training set of ten distinct samples. (A vector format describes the mapping of all the nodes of one layer to another, while a matrix format allows a connection scheme to map nodes from one layer to one or more nodes of another.) This report also describes the steps in the development process including the construction of a training set, the creation, initialization, and training of a neural net, the testing of how accurate the neural network filtered noisy 2-D images, and the preparations involved to retrain a neural network. A description of the development and use of objective and subjective criteria in determining how accurate the net filtered noise to produce a noise-free image is also included.

The study concludes with a summary of the experiment, including determining the best neural network architectures used in filtering noise, the type of scaling which gives the best performance, what image size provides the best results, and what effect recursion has on neural networks (or how many times should an image be filtered through a net to produce a noise-free image.) It was determined that it is feasible to utilize neural networks to filter noisy 2-D data to provide a recognizable image of the original noise-free data. A matrix architecture consisting of input and output layers of equal size, and one middle layer, should be used. The size of the images used to test and train the network should consist of 300, 400, 500, and 600 nodes, where each node represents a pixel of the image. If a specific image was used to train the network to recognize patterns, the neural net will filter noise to produce an image correct in orientation, location, and shape to the corresponding noise-free image. Otherwise, if the neural network had trouble filtering enough noise to produce a clean image, and if the image was not part of the training set, recursion may help generate an image correct in orientation, location, and shape.

1. INTRODUCTION

The purpose of this study was to determine if neural networks could perform a non-linear filtering operation to remove noise from two-dimensional (2-D) input data, resulting in a 2-D noise-free image. This report discusses the steps involved in the constructing, training and utilizing of a neural network, and presents the findings.

2. METHODOLOGY

2.1. Definition and Uses of Neural Networks.

A neural network is a web of interconnected processing elements, called nodes, patterned in a highly interconnected parallel structure. The network may be set up as a computer program to model the interaction of these nodes similar to those in the brain. A neural network by itself does not have the ability to improve performance. Rather, it is a program, such as NETS (see section 2.2), external to the network that improves performance by using the architecture of the neural network as a model. Improved performance is achieved through a process of teaching or training the network. This process evaluates the connections between the nodes - called weights - to minimize the prediction error.

As a branch of artificial intelligence, neural networks are used in a variety of commercial and military applications, including data segmentation, data compression, signal filtering, and pattern detection. Appendix A contains several definitions which may be useful to those not familiar with neural nets.

2.2. Software Used.

This study used a software package called NETS, a neural network simulator developed by Paul T. Baffes in the Artificial Intelligence Section (now called the Software Technology Branch) of NASA's Johnson Space Center. The primary function of the simulator includes a flexible system that utilizes the generalized delta feed-back propagation learning method without the need for specialized hardware. NETS is an interpreter, with its "read-evaluate-print" method of execution similar to other computer languages such as BASIC and LISP. The simulator presents a menu of 16 options to the user and prompts the user for a command. After issuing the command NETS will attempt to evaluate the command, which may produce more prompts requesting specific information or an error messages if the command is not understood. The data presented in this report was generated using a Compaq 386 personal computer with a math coprocessor. Training times are expressed in seconds. The image data files used in this study consist of scaled integers, which appears to limit the size of the pattern array[1] due to the limited numerical precision of integer arithmetic.

2.3. Setting up the architecture

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[1] The precision of the arithmetic using scaled integers has been demonstrated to be insufficient for convergence of the back-propagation algorithm in other applications. However, the size of the training sets and the limited amount of computer memory in the Compaq 386 meant that only scaled integers could be used in this study.

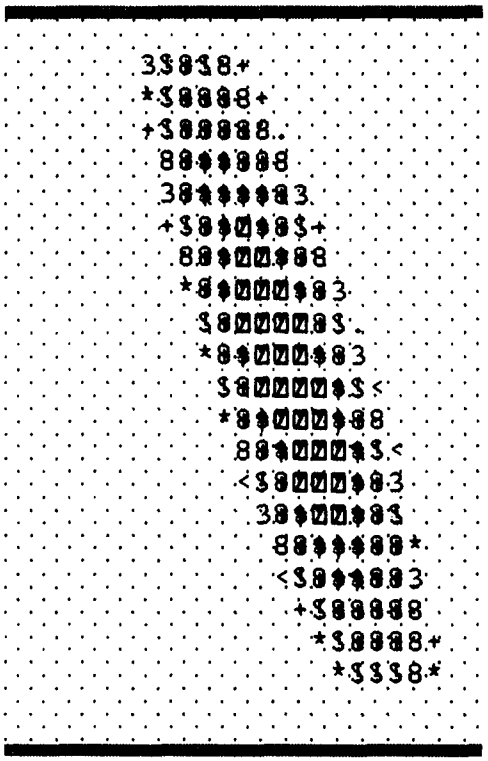

Diagram 1: Sample of a noise-free image.

2.3.1. Getting started.

The first stage of the study involved finding an optimal architecture for performing experiments, using 25-by-20 node subsections of noisy and noise-free image data, with each subsection derived from 69-by-39 node image data with and without noise. The images were obtained from a project that attempted to identify defects in cast explosives, and were generated by a model developed by Mr. George Schlenker, which simulated X-ray images of cast explosives. An example is shown in Diagram 1. The noisy image data is used as input to the neural net and the clean image data represents the desired output. Therefore, each sample that comprises the training set used to train the network will consist of a noisy and a clean image of the same pattern. Each image is 500 nodes in size (25 nodes by 20 nodes). The architecture of the neural net consists of layers - an inner layer, an outer layer, and one or more middle layers. The inner and outer layers are made up of 500 nodes while the middle layers may vary in size. When NETS begins training the network, it will attempt to converge to an user-defined max absolute constraint error value. This value typically is as low as 0.1 or as high as 0.2, depending upon the size of the training set. The objective is to have the neural net filter enough noise from as many different types of images as possible. A higher error constraint would improve generalization but sacrifice accuracy; conversely, a lower error constraint would improve accuracy at the expense of generalization. The desirable error constraint was preset to 0.1. Furthermore, a good indication if a neural net is learning to filter noise from samples in the training set (and therefore converging) is when the root mean squared (RMS) error dropped below 0.1. Finally, several input specifications are required to configure the net before training commences. These include maximum and minimum weight values, learning rates, momentum, and bias. NETS uses global defaults on all of these specifications, but the user has the option of changing these defaults, both globally and for specific layers.

The first architecture considered consisted of a straight vector format - that is, each of the nodes of one layer is connected to each of the nodes of the next layer of the network. This means that all of the nodes from the input layer are connected to each of the nodes of the middle layer, and in turn all of the nodes of the middle layer are connected to each of the nodes of the output layer. The initial size of the middle layer was computed as 2 plus the square root of x, where x equals the number of input layer plus the number of output layer nodes. Since the size of both layers is 500 nodes, the value of x in the above equation is 500. Therefore, it was determined that 35 nodes should be used to compose the middle layer. The architecture of the vector network is as follows:

```
   Layer 0          Layer 1          Layer 2
(Inner Layer)---->(Middle Layer)---->(Outer Layer)
  500 Nodes        35 Nodes         500 Nodes
```

The plan was to train the network to filter noise from image data starting from a training set of

one sample. As specific networks were successfully trained, additional samples (up to a maximum of ten) would be added. Using a training set of one sample, the vector network did not "learn" enough to filter noise to produce an acceptable image, despite changing training factors such as momentum and weights; increasing the number of training cycles and changing the number of middle layers did not facilitate the training of the network.

2.3.2. Starting with a matrix format.

At this point it was realized that a different architecture was needed to train the network. Based on past experience with other models it was decided to utilize a matrix format. The difference between a matrix format and a vector format is that a matrix format allows for patterned connection schemes between layers, as opposed to using the fully connected scheme. In other words, a group of nodes that lie close together in one layer may be mapped to a single node in another layer. In this way, the neural network pieces together bits of visual information by trying to build larger shapes out of smaller regions of a particular image. The matrix format for the new net architecture was set up as follows:

	Layer 0 (Inner Layer)	---->	Layer 1 (Middle Layer)	---->	Layer 2 (Outer Layer)
	500 Nodes		8 Nodes		500 Nodes
Image Size:	(25 x 20)		(4 x 2)		(25 x 20)
Block Pattern:	(10 x 10)				
Overlap[2]:	(5,0)				

Using a training set of one sample, the NETS package trained the network to converge to a max absolute error constraint of under 0.1 in less than five seconds, successfully filtering enough noise to produce a recognizably clean image. Additional changes were made by changing global weights, changing global momentum, and incorporating bias, with the result that the net did learn at a faster rate, but these changes made no significant difference in the quality of learning. Several training sessions were completed using a variety of middle layer sizes and pattern sizes. The following table provides an initial summary of results (using a training set of one sample):

---

[2] For a better explanation of matrix format in neural nets please go to Appendix A, Section 2 or, if available, the **NETS User's Guide**, Version 2.0, pgs. 15-24.

Table 1: One Training Set, Various Pattern and Middle Layers						
Size of Blocking Patterns	Size of Middle Layer	Size of Overlap	Max Abs Error	RMS Error	Number of Cycles	Learning Rate (secs)
9 x 10 (90)	3 x 2 (6)	(1,0)	0.097	0.070	11	4.0
7 x 10 (70)	4 x 2 (8)	(1,0)	0.081	0.044	9	4.0
5 x 10 (50)	5 x 2 (10)	(0,0)	0.067	0.024	7	3.0
9 x 5 (45)	3 x 4 (12)	(1,0)	0.076	0.036	6	4.0
7 x 5 (35)	4 x 4 (16)	(1,0)	0.072	0.018	5	3.0
5 x 5 (25)	5 x 4 (20)	(0,0)	0.068	0.026	4	3.0

It appears that increasing the number of nodes in the middle layers while decreasing the pattern size may decrease the max absolute error and RMS error (and therefore train the network). However, this can be accomplished by lowering the maximum weight value during the creation of the net. This observation led to another question: what size of overlap pattern and middle layer provides the best type of architecture for the neural net? The next step was to determine the effects of modifying pattern and overlap sizes, while increasing the middle layer size, in the development of a more accurate neural network. A training set of three samples was used here. The results are categorized in the following table:

Table 2: Various Patterns, Overlaps, and Middle Layers Used for a Training Set of Three Samples						
Size of Pattern Blocks	Overlap Layer	Middle Layer	Max Abs Error	RMS Error	Number of Cycles	Learning Time (sec)
9 x 10	(1,0)	3 x 2	0.091	0.058	10	5.0
	(5,0)	5 x 2	0.088	0.055	9	5.0
	(1,5)	3 x 3	0.075	0.021	9	5.0
	(5,5)	5 x 3	0.094	0.024	9	7.0
9 x 8	(1,4)	3 x 4	0.094	0.024	10	6.0
	(5,4)	5 x 4	0.086	0.027	6	6.0
7 x 10	(1,0)	4 x 2	0.073	0.044	9	4.0
	(1,5)	4 x 3	0.088	0.018	8	5.0
	(4,0)	7 x 2	0.080	0.018	8	6.0
	(4,5)	7 x 3	0.079	0.018	6	5.0

Table 2 continues on next page:

Table 2 (continued)

Size of Pattern Blocks	Overlap Layer	Middle Layer	Max Abs Error	RMS Error	Number of Cycles	Learning Time (sec)
7 x 8	(1,4)	4 x 4	0.081	0.031	7	5.0
	(4,4)	7 x 4	0.083	0.017	5	6.0
5 x 10	(0,0)	5 x 2	0.088	0.020	8	4.0
	(1,0)	6 x 2	0.098	0.034	6	4.0
	(0,5)	5 x 3	0.085	0.029	7	5.0
	(1,5)	6 x 3	0.086	0.040	5	5.0
9 x 5	(1,0)	3 x 4	0.067	0.018	6	4.0
	(5,2)	5 x 6	0.083	0.040	4	5.0
5 x 8	(0,4)	5 x 4	0.077	0.025	5	4.0
7 x 5	(1,0)	4 x 4	0.082	0.023	5	4.0
	(1,2)	4 x 6	0.082	0.025	4	4.0
5 x 5	(0,0)	5 x 4	0.070	0.022	4	4.0

The results were inconclusive. By reducing the pattern size the neural net appeared to have been trained with great accuracy, but only if maximum weight values are kept down to about 0.15 to 0.20. The best results indicated that if a pattern between 50 and 90 nodes in size is mapped to a middle layer of less than 20 nodes, the net will be trained quickly without any problems. If the size of the middle layer is greater than or equal to 20 nodes, the maximum global weight selected during the creation of the net must be decreased or else the net will fail to learn. Employing bias on such a small middle layer size does not make a difference.

2.3.3. Adding middle layers.

The next step was to investigate the incorporation of additional middle layers to determine if the net will converge faster while increasing the number of samples in the training set. A variety of neural network architectures for up to 3 input data sets was tested. It was found that a middle layer of 35 nodes supplemented with another middle layer of 16, 20, or 25 nodes will converge under 100 cycles, either with or without bias. The conclusion is that a variety of network architectures exist than can be used to train a net to handle a training set of 3 examples, but only if the maximum error constraint was set to 0.2. Appendix B.1 lists all of the architectures tested. Those network architectures that produced a trained network are listed below:

Table 3: List of Network Architectures using a Training Set of 3 Samples

Pattern	Overlap	Size	Max Abs Error	RMS Error	Cycles	Learning Time (secs)
with bias, 1 middle layer:						
5 x 8	(0,6)	5 x 7	0.197	0.050	24	105.0
7 x 4	(4,0)	7 x 5	0.182	0.059	23	98.0
without bias, 1 middle layer:						
7 x 4	(4,0)	7 x 5	0.182	0.059	23	142.0
with bias, 2 middle layers:						
1: 5 x 8 2: 1 x 4	(0,6) (0,3)	5 x 7 5 x 4	0.181	0.059	46	164.0
1: 5 x 8 2: 2 x 3	(0,6) (1,2)	5 x 7 4 x 5	0.187	0.060	90	273.0
1: 9 x 8 2: 1 x 4	(5,6) (0,3)	5 x 7 5 x 4	0.190	0.088	86	275.0
1: 9 x 8 2: 1 x 3	(5,6) (0,2)	5 x 7 5 x 5	0.193	0.067	89	334.0
1: 9 x 8 2: 2 x 4	(5,6) (1,3)	5 x 7 4 x 4	0.198	0.073	98	277.0
1: 9 x 8 2: 2 x 3	(5,6) (1,2)	5 x 7 4 x 5	0.199	0.087	76	not recorded
1: 7 x 4 2: 3 x 2	(4,0) (2,1)	7 x 5 5 x 4	0.198	0.066	95	282.0
1: 7 x 4 2: 3 x 1	(4,0) (2,0)	7 x 5 5 x 5	0.198	0.055	52	189.0
Without bias, 2 middle layers:						
1: 5 x 8 2: 1 x 4	(0,6) (0,3)	5 x 7 5 x 4	0.195	0.052	44	155.0
1: 5 x 8 2: 1 x 3	(0,6) (0,2)	5 x 7 5 x 5	0.197	0.058	49	149.0
1: 5 x 8 2: 2 x 4	(0,6) (1,3)	5 x 7 4 x 4	0.197	0.051	45	118.0

Table 3 continues on next page:

Table 3 (continued)						
Without bias, 2 middle layers (continued):						
Pattern	Overlap	Size	Max Abs Error	RMS Error	Cycles	Learning Time (secs)
1: 5 x 8 2: 2 x 3	(0,6) (1,2)	5 x 7 4 x 5	0.199	0.044	81	222.0
1: 9 x 8 2: 1 x 4	(5,6) (0,3)	5 x 7 5 x 4	0.199	0.066	65	203.0
1: 9 x 8 2: 2 x 4	(5,6) (1,3)	5 x 7 4 x 4	0.192	0.060	64	181.0
1: 9 x 8 2: 2 x 3	(5,6) (1,2)	5 x 7 4 x 5	0.196	0.065	65	208.0
1: 7 x 4 2: 3 x 2	(4,0) (2,1)	7 x 5 5 x 4	0.188	0.077	43	133.0
1: 7 x 4 2: 3 x 1	(4,0) (2,0)	7 x 5 5 x 5	0.199	0.063	30	110.0
1: 7 x 4 2: 4 x 2	(4,0) (3,1)	7 x 5 4 x 4	0.195	0.060	34	89.0

We found that there are a variety of architectures that can be developed using one or two middle layers. The best results involved two middle layers: one 35 nodes, the other 16, 20, or 25 nodes in size. All of these architecture converged under 100 cycles, with or without bias.

2.3.4. Experiments with various size training sets

2.3.4.1. Comparisons of training sets of three and five samples

After identifying an optimal architecture that used a training set of three samples, additional work was needed to determine if this architecture could be used to train a network with a training set of five samples. Using the architecture of one middle layer and incorporating a bias, forty image data were filtered and the results displayed for visual inspection through a grey-scale program. It was apparent that the neural network architectures that successfully converged using a training set of three samples do not work well for a training set of five samples. At this point more work was needed to identify a neural network architecture that is able to properly filter noise. The architecture that used a training set of three samples produced the following results for a training set of five samples:

Table 4: Result of using a Set of 5 Samples on an Optimal Architecture for 3 Training Samples					
Number of Training Sets	Preset Error Constraint	Max Abs Error	RMS Error	Number of Cycles	Time (sec)
5	0.2	0.481	0.140	100	n/a

These numbers confirmed that the net did not converge and thus could not identify noisy data. If an image data file was propagated through this net and its image compared with its corresponding clean image, it would become obvious that these images do not look alike in shape and form. The same architecture that successfully converged using a training set of three samples could not converge using a training set of five samples. Therefore, in order for the network to develop the ability to detect patterns, the architecture of the network must be modified and trained with more examples.

2.3.4.2. Using five- and ten-sample training sets.

At this point a new architecture had to be developed to handle five training sets. Furthermore, with more training samples to learn, it was apparent that a small middle layer would not provide the desired results. What needed to be done was to increase the number of nodes in the middle layer and perhaps increase the number of middle layers in the architecture to two or three. If these measure did not work, the size of the training files was reduced from 500 to 400 nodes for computational economy. Several architectures were developed and trained using a training set of five examples. These architectures are listed in Appendix B.2. The following architectures; incorporating one middle layer and a bias, provided the best results, converging under a preset constraint error of 0.2:

Table 5: Architectures that provided the best results Using a Training Set of 5 Samples (and bias)						
Size of Pattern Layer	Overlap Layer	Middle Layer	Max Abs Error	RMS Error	Number of Cycles	Learning Time (sec)
9 x 4	(5,2)	5 x 9	0.194	0.061	27	238.0
5 x 2	(0,0)	5 x 10	0.188	0.043	76	695.0
9 x 2	(5,0)	5 x 10	0.175	0.062	30	296.0
7 x 4	(5,0)	10 x 5	0.196	0.048	43	407.0

One architecture that did not use a bias was found to be able to train a network to a maximum error of 0.1 in under 150 cycles. Its characteristics are as follows:

Table 6: Architectures that provided the best results Using a Training Set of 5 Samples (no bias)						
Size of Pattern Layer	Overlap Layer	Middle Layer	Max Abs Error	RMS Error	Number of Cycles	Learning Time (sec)
5 x 4	(0,2)	5 x 9	0.100	0.039	132	1043.0

None of the neural network architectures employing two or more middle layers converged to an error less than 0.2. It is apparent that the best neural network architecture to filter noisy data consists of only one middle layer. From a collection of architectures employing one middle layer, the one that produced the lowest maximum error should be used to test a training set consisting of up to ten samples. The results of incorporating an additional set to the architecture described above are shown as follows:

Table 7: Results of Incorporating Additional Samples into the Training Set					
Number of Samples in Set	Number of Cycles	Selected Constraint Error	Max Abs Error	RMS Error	Learning Time (sec)
No bias:					
5	26	0.2	0.196	0.057	224.0
	+100	0.1	0.171	0.045	---
6	21	0.2	0.194	0.050	192.0
	+100	0.1	0.149	0.040	---
7	100	0.2	0.352	0.045	---
	+100	0.1	0.147	0.040	---
8	100	0.2	0.223	0.038	---
	+32	0.2	0.197	0.056	383.0
	+100	0.1	0.149	0.043	---
10	300	0.2	0.891	0.258	---
bias:					
5	38	0.2	0.171	0.048	324.0
	+100	0.1	0.159	0.037	---

Table 7 continues on next page:

Table 7 (continued):					
bias (continued):					
Number of Samples in Set	Number of Cycles	Selected Constraint Error	Max Abs Error	RMS Error	Learning Time (sec)
6	76	0.2	0.193	0.044	n/a
	+100	0.1	0.171	0.041	---
7	38	0.2	0.198	0.058	n/a
	+100	0.1	0.154	0.036	---
8	100	0.2	0.665	0.171	---
	+23	0.2	0.199	0.048	290.0
	+100	0.1	0.891	0.258	---

It appears that 500-node image data files are too large to determine the right type of architecture for the neural net to filter noise so 400-node image data files were used to train the net. The most optimal architecture that produced a trainable net is displayed below:

	Layer 0 (Inner Layer)	---->	Layer 1 (Middle Layer)	---->	Layer 2 (Outer Layer)
	400 Nodes		45 Nodes		400 Nodes
Size:	(20 x 20)		(5 x 9)		(25 x 16)
Pattern:	(4 x 4)				
Overlap:	(0,2)				

3. Establishing criteria

To determine if a neural network adequately filtered noise to produce a recognizable image, there must be a way to visually and statistically determine such a measure of success. Two such criteria, subjective and objective, were established and are described below. A summary of the results is listed in Appendix B.

3.1. Subjective criteria

A grey-scale program producing 12 shades of grey is available to produce a picture of image data files propagated through a trained neural network. The program transforms each node into a shade of grey in the image, using a direct interpolated relationship, which depend upon the range of values represented by the image data file. If a value fits within a certain range representing a shade of grey, the program prints that shade of grey to represent the node. The pictures generated represent a visual composite of the matrix. The grey scale program can also be used to create image data files from a series of prompts generated by the program. These files may be used as training or test sets.

The outputs generated by this program may be described using the size (300, 400, 500, or 600

nodes), orientation (slanted left, straight, slanted right, or undeterminable), location of the center (top, center, or bottom), and shape (oval, half oval, roughly oval, roughly half oval, x-shaped, or amoebic). During the development of the network architecture, pictures of the filtered image data files were generated by the grey-scale program and visually compared with their corresponding clean images.

3.2. Objective criteria[3]

The fraction of squared residuals (FSR) is a revised, scale-invariant method for determining how successful the neural net filtered noise from propagated input data. A "C" program was written and compiled to generate a value, given two input files, either the noisy and clean samples or the filtered (propagated) and clean samples. (The values generated by this program are compared with each other to determine if the filtered image data file is an improvement over the original noisy image data file.) If the FSR value generated by the program is equal to zero, then the filtered sample is an exact match of the clean sample. The cutoff value was selected to be 0.25. At higher FSR values, based on visual comparison of the subjective criteria, the shape of the filtered image does not resemble the clean sample of the same set.

4. Experiments with 300-, 400-, 500-, and 600-node samples.

After selecting the best performing network architectures, experiments were performed to determine how successfully this neural net filtered noise. A total of 19 samples (10 training, 9 non-training) were filtered through each trained network. These samples were composed of combinations of various orientations, locations of the center, and shapes of images of truncated ellipsoids composed of varying numbers of nodes. All of the samples used in these experiments, with three exceptions, are oval-shaped; the three exceptions are half-oval (truncated ellipses) in shape and are referred to in this report as partial patterns. These combinations, shown in Appendix C, paragraph C.1. Paragraph C.2, lists the actual outcomes for each network. The results of those experiments are discussed below.

4.1. Describing images

In determining how successful the neural net filtered noise from data, it is important to visually inspect the results. This was done using the grey scale program, which generated a visual representation of input (noisy), filtered, and clean images for all of the sample sets. The grey-scale images of complete ellipsoids appear as holes in the plane. These figures are displayed in Appendix C, sections C.4.1 to C.4.4. An example of one set of these images is shown here for convenience (see Diagrams 2a-2d on next page):

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[3] Because human vision displays a logarithmic brightness sensitivity, it is tempting to construct a measure of image fidelity as an average over all corresponding nodes, of decibel (dB) differences between noisy and noise-free data sets. A quantitative measure of quality of restoration was developed by my colleague George Schlenker on this basis. However, a basic assumption of this approach - identical scales for both images - was not satisfied due to (uncontrolled) non-linearity of network filtering. Consequently, a second measure was developed to include nonlinearity - the fraction of squared residuals (FSR).

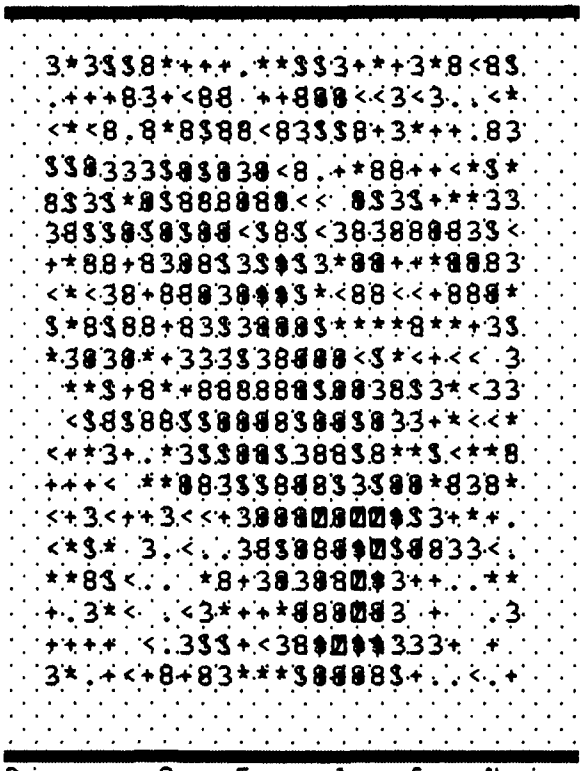


Diagram 2a: Example of a Noisy Image.

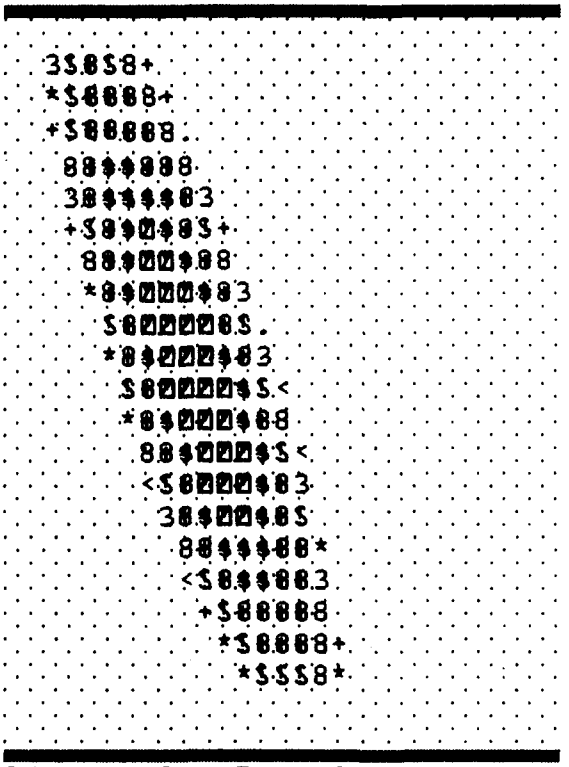


Diagram 2b: Example of a Noise-free image.

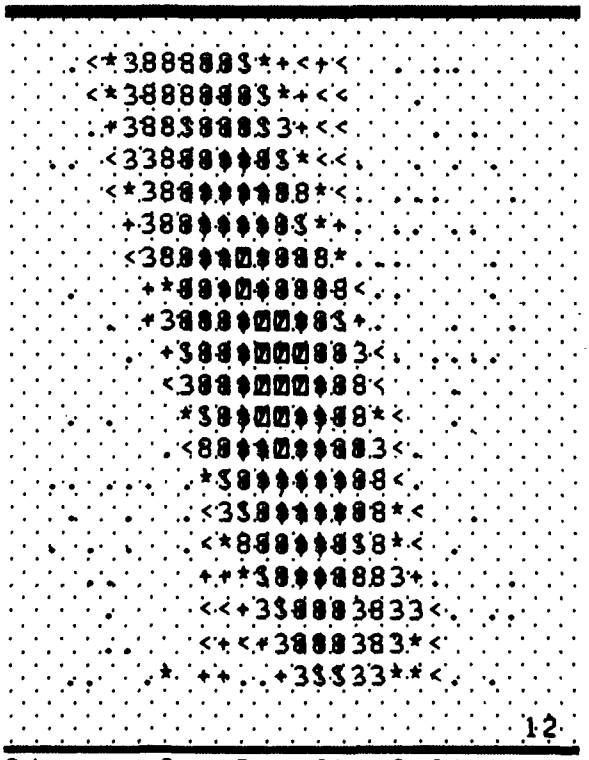


Diagram 2c: Result of first recursion of noisy image.

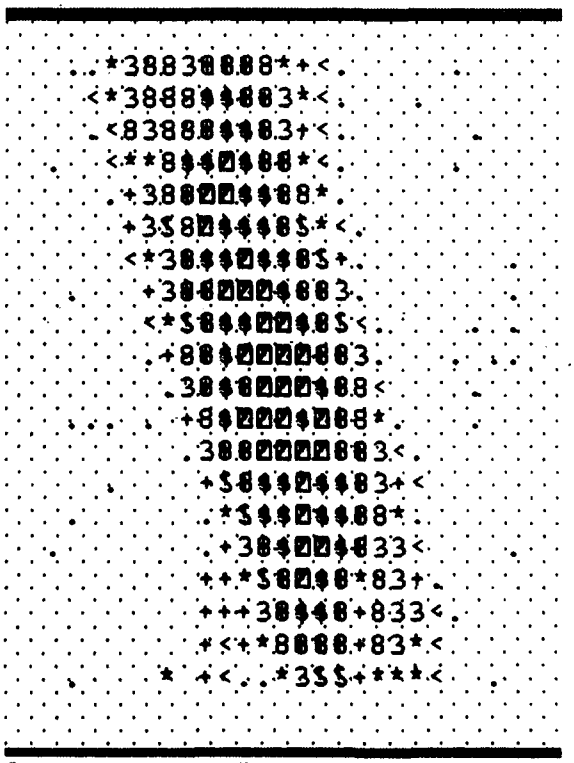


Diagram 2d: Result of performing second recursion of image.

The images are described using three parameters: orientation (O), location of center (L), and shape of the image (S). The following table displays an example of one of the sets of images[4]

	Set	O	L	S	FSR
(Set 1 - noisy images)	1a	L	C	0	.9155
(after original propagation)	b	L	C	0	.1547
(with one recursion)	c	L	C	0	.1259
(with additional recursion)	d	-	-	-	----

In the example above, the first line (a) describes the appearance of the clean image for set 1 and the FSR value result of comparing the noisy image for set 1 with the clean image for the same set. The second line (b) describes the shape of the image after propagating the noisy image through a trained neural net and the FSR value of the propagated vs. clean image. The third line (c) describes the shape of the image after one recursion and the FSR value of the image vs. the clean image. If recursion was performed again, the description of the image and its corresponding FSR value would be described in the last line. All of the images were generated using a gray-scale program. To determine if the net successfully filtered enough noise, the propagated image must match the clean image in orientation, location of center, and shape. If the FSR value generated is less than 0.25, the visual representation of the filtered image will be similar to that of the clean image. A table of results for all sets are found in Appendix C.

4.2. Absolute versus Relative Scaling

When generating image data for use in the NETS program, the nodes that comprise the image must be scaled to values between 0 and 1. Scaling requires a maximum and minimum value of image data. The choice of range R can be made in either of two ways. These are referred to here as "relative scaling" and "absolute scaling". Both absolute and relative scaling were used in the construction of the image data used in the network. In general, the range (R) is defined as the difference

$$\max(\text{intensity value}) - \min(\text{intensity value})$$

Absolute scaling imposes the same scale on all images using the maximum and minimum values of the set of images before performing scaling operations upon each image. Relative scaling, on the other hand, permits a unique scale for each image based on the maximum and minimum value of the image before performing scaling operations. Image data based on absolute scales were used only during testing of architectures using 400-node images; the rest of the image data are based on relative scaling.

4.3. Testing with various size samples

[4] A complete explanation of all symbols used to describe the appearance of the images is found in Appendix C.

4.3.1. Testing with 300-node relative samples.

The architecture used to generate this network is as follows:

	Layer 0 (Inner Layer)	Layer 1 (Middle Layer)	Layer 2 (Outer Layer)
	300 Nodes	45 Nodes	300 Nodes
Image Size:	(25 x 16)	(5 x 9)	(25 x 16)
Block Pattern:	(5 x 7)		
Overlap:	(0,6)		

Of the nine non-training, relative-scale samples, the net filtered noise from five samples. Recursion of the remaining samples improved the resolution of their images. It also appeared that the network can be trained to detect the shape and orientation of a particular sample. None of the partial image data propagated through the net were filtered successfully. The impact of the partial image data is that the net can filter more noise from image data if the net detects a recognizable pattern in the noisy image data during propagation. The FSR values generated for these images range from 0.0109 to 1.685, with the successful values not exceeding 0.2215. The highest FSR values were generated for those samples whose clean image represented only part of a recognizable pattern. For those samples that constitute the training set the net filtered noise to produce a pattern correct in shape, location of center, and orientation of the image. However, recursion slightly worsened the quality of those images. The FSR values generated for the training images range from 0.0111 to 0.1204.

Gray-scale images generated for 300-node images are located in Appendix C, section C.4.1.

4.3.2. Testing with the 400-node absolute and relatively scaled samples

The architecture used to generate this network is as follows:

	Layer 0 (Inner Layer)	Layer 1 (Middle Layer)	Layer 2 (Outer Layer)
	400 Nodes	45 Nodes	400 Nodes
Image Size:	(20 x 20)	(5 x 9)	(25 x 16)
Block Pattern:	(4 x 4)		
Overlap:	(0,2)		

With all samples (those that constitute the training set and the remainder that did not) the neural network weight calculations did converge for both relative and absolute scales. However, for all of the image data based on the absolute scale, (both training and non-training sets) propagation only resulted in producing more noise, producing a pattern as if one was spreading a glob of jam on bread. Recursion did not improve the pattern, and the image produced was worse than the original.

The FSR values generated for all of these images reflected the subjective results; the values range from 0.2586 to 1.3432, with the majority of the measurements over 1.22.

With the images using relative scale, the neural network filtered noise to produce a clean pattern from all of the training samples and two of the nine non-training samples. Recursion improved the appearance of four patterns (two each from the training and non-training set) but in general worsened the appearance of the filtered image. The FSR values generated from the

propagated set ranged from 0.1531 to 1.028 and range from 0.1640 to 1.387 for those generated through recursion, with the highest FSR values belonging to the partial patterns.

Gray-scale images generated for 400-node images are located in Appendix C, section C.4.2.

4.3.3. Testing with 500-node relative samples.

The architecture used to generate this network is as follows:

	Layer 0 (Inner Layer)		Layer 1 (Middle Layer)		Layer 2 (Outer Layer)
	500 Nodes	---->	45 Nodes	---->	500 Nodes
Image Size:	(25 x 20)		(5 x 9)		(25 x 20)
Block Pattern:	(5 x 4)				
Overlap:	(0,2)				

Six of the non-training samples produced a pattern similar in shape, location of center, and orientation to the corresponding clean image. Recursion worsened the appearance for most of these images. FSR values generated for the propagated images range from 0.0121 to 1.353, with the recursion samples ranging from 0.0260 to 1.414. The partial patterns produced the highest FSR values; if these images were not taken into account, the highest FSR value generated would be 0.3073. The net successfully filtered noise from the images for all of the training files, which were correct in orientation, location and shape; but recursion worsened their appearance. The range of FSR values range from 0.0104 to 0.2031.

Gray-scale images generated for 500-node images are located in Appendix C, section C.4.3.

4.3.4. Testing with 600-node relative samples.

The architecture used to generate this network is as follows:

	Layer 0 (Inner Layer)		Layer 1 (Middle Layer)		Layer 2 (Outer Layer)
	600 Nodes	---->	45 Nodes	---->	600 Nodes
Image Size:	(25 x 24)		(5 x 9)		(25 x 24)
Block Pattern:	(5 x 8)				
Overlap:	(0,6)				

For all but one of the non-training samples, the net did not filter enough noise to produce a clean pattern, nor did recursion improve the image. The FSR values for non-training samples range from 0.2358 to 1.6329. In some cases the FSR value generated from noisy vs. clean image comparison was lower than the FSR value generated from propagated vs. clean image comparison. The net did filter noise from all of the training samples to produce images with correct orientation, location, and shape. The FSR values generated for the training sets range from 0.0137 to 0.2990, with most of the values less than 0.025.

Gray-scale images generated for 600-node images are located in Appendix C, section C.4.4.

4.4. Results of experiments

4.4.1. Summary of samples in the training sets.

With few exceptions, the number of nodes in each examples within the training sets is irrelevant when filtering noisy data. Only one propagation is required to produce the desired image, but recursion may be used if the net has trouble filtering noise. In such a case one recursion operation should be used or else the net will not be able to filter noise well enough to produce a clean image.

4.4.2. Summary of samples in the non-training sets.

In most cases the net filtered enough noise to produce a pattern similar in shape, orientation, and location of center to that of the clean image. If recursion was used, only one iteration was required. None of the partial images were successfully filtered by the net. The sample size that produced the best results consisted of 500 nodes.

4.4.3. Summary

Within the size range studied, for the size of the image constituting a training set, the net will filter noise to produce an image correct in shape, orientation, and location of center. As for the image data that make up the non-training set, the net performed best using 500-node samples. To test the success of filtering noise from sample data, it is critical that the most important pattern of interest (i.e. the ellipsoid) should be centered in the middle. In other words, the more there is of a pattern for the net to recognize, the better the chance of the net to correctly reproduce that pattern. For most cases, recursion worsened the appearance of those images that were part of the training set but may improve the appearance of non-training images.

5. CONCLUSIONS

5.1. Developing a neural network architecture

To summarize, the development of a neural net architecture consists of the following steps:

a) Construct a training set of samples of equal size, where each sample represents data for an unfiltered image and an image without noise.
b) Create and train the neural network to the lowest possible error constraint.
c) Save the weights created during training to a file.
d) Test by propagating samples through the neural net. These samples may consists of those used in the training set and those that are not. The images of the propagated patterns should be generated using a grey-scale program and the results visually compared with the clean image.
e) Before increasing the size of the training set save the weights generated by the neural net to a weight file. The data file containing the training set can only be modified outside of NETS.
f) Increase the size of the training set by one sample. This should enable the neural net to learn more patterns.
g) Before retraining the network it is important to load the weight file saved from the previous experiment.

After determining how many samples should be in the training set it is important to select the network architecture that will produce the best results. The above description should help clarify the process.

5.2. Conclusions drawn from experiments

Several conclusion can be drawn from these experiments.

a) A matrix architecture consisting of one middle layer should be used to filter noisy data. The size of the image data used to test and train the neural network should consist of 300, 400, 500, or 600 nodes.

b) Images based on relative scale should be used to train and test the neural net for this application.

c) With regard to those images used in the training set and filtered through a trained neural net, the number of nodes in each sample is irrelevant. The neural net will filter noise to produce an image correct in orientation, location and shape to the corresponding clean image. The only way that the trained net can recognize a specific pattern is to incorporate that pattern as part of the training set.

d) The 500-node size provided the best results with non-training examples.

e) If the neural net had trouble filtering noise to produce a clean image, and if the subject example was not part of the training set, recursion may help generate an image with the correct orientation, location, and shape. Only one propagation is required to provide a better resolution for any particular example. Recursion of samples used in the training set only worsens the appearance of the image.

Appendix A: Terminology

This appendix provides only the minimum explanation needed to understand the material presented in this report. For more information consult the NETS User's Guide (Version 2.0).

A.1. Definitions

bias - a bias value are weight values used to offset (hence "bias") the output value of a node.

cycles - represents the number of times the training set presents itself between neurons to settle into a stable pattern in order to connect or classify input patterns.

error - represents the difference between the current state of the network and the desired state to produce a function (sum of squared errors) utilized to perform the gradient descent to change the weights of the network.

FSR (Fraction of Squared Residuals) - a scale-invariant method used to measure the quality of an image. Two input files are used to generate this value. If the FSR generated is equal to zero, then the filtered sample is an exact match of the clean sample.

The equation for FSR is developed as follows:

Let $Z(i)$, $i = 1, \ldots, m$ represent the noise-free patterns, and $Z_n(i)$, $i = 1, \ldots m$ represent the noisy patterns.

Define the following auxiliary variables:

$$\overline{Z}=\frac{1}{m}\sum_{i=1}^{m} Z(i) \qquad \overline{Z_n}=\frac{1}{m}\sum_{i=1}^{m} Z_n(i)$$

$$S_Z^2=\frac{1}{m}\sum_{i=1}^{m} (Z(i)-\overline{Z})^2 \qquad S_{Z_n}^2=\frac{1}{m}\sum_{i=1}^{m} (Z_n(i)-\overline{Z_n})^2$$

Then calculate the standardized versions of $Z(i)$ and Z_n. Call these $\zeta(i)$ and $\zeta_n(i)$:

$$\zeta_1(i)=\frac{Z(i)-\overline{Z}}{S_Z} \qquad \zeta_{1_n}(i)=\frac{Z_n(i)-\overline{Z_n}}{S_{Z_n}}$$

Finally, the Fraction of Squared Residuals (FSR) of the standardized residuals is obtained by:

$$FSR=\sum_{i=1}^{m} \frac{(\zeta(i)-\zeta_n(i))^2}{m}$$

global - refers to setting specific momentum, learning, and weight values for all layers of a neural net.

image - refers to a pictoral representation of image data. (See definition below.)

image data - refers to a data file of scaled values indexed between 0 and 1. Image data files are used by NETS to set up training files and for testing how successfully the neural network learned.

layers (also called slabs) - refers to a grouping of nodes. In this experiment the neural networks used will have an input layer, an output layer, and one or more middle (or hidden) layers. The input layer presents the stimuli to commence training of the network and the output layer determines the network's response.

learning - the network achieves learning by changes in the weight values.

learning rate - this parameter is used to change the connection strengths (i.e. the weights) between the nodes.

local - refers to setting momentum, learning, and weight values for specified layers of a neural net.

momentum - enhances the speed of learning by adding in past effect of weight changes to produce similar alterations in a weight, building up a collective momentum to change the value of the weight more rapidly.

node (also called a processing element, pixel or neuron) - the basic processor of a neural network roughly analogous to a biological neuron. The node calculates incoming connection values to calculate its output through the use of some threshold scheme.

overlap - refers to overlapping pattern areas when mapping a group of nodes from one layer onto a single node in another (see pattern).

pattern - refers to pattern areas of an incoming (outer) layer being mapped as a group onto a single node of the current (inner or next) layer.

propagation - this is the process of taking a noisy image through a trained net and filtering noise to produce an image, i.e., calculation of output from input.

recursion - refers to the process of refiltering an image previously propagated through the net by propagating this image through the net one more time.

teaching (or training) - refers to presenting a set of data to a neural network, where this data will cause the weight values of the network to change in response to the input.

weight (also called connections) - a value which represents the connection carrying the electrical between nodes.

A.2. Explanation of matrix formation in neural nets

The NETS program permits a matrix architecture to be created in which a 2-D input array is organized into 2-D blocks for the purpose of making connections to each of the nodes of the

middle layers. The process of "blocking" involves several parameters:

X_{big} - The number of rows in the input pattern.
$X_{pattern}$ - The number of rows per block
$X_{overlap}$ - The number of row elements overlapped in adjacent blocks
X_{small} - The number of row-wise blocks

Y_{big} - The number of columns in the input pattern.
$Y_{pattern}$ - The number of columns per block
$Y_{overlap}$ - The number of columns elements overlapped in adjacent blocks
Y_{small} - The number of column-wise blocks

For the moment consider only one row of blocks. To evaluate the number of column blocks (Y_{small}), recognize that the Y_{big} columns in the pattern must equal $Y_{pattern}$ elements in an end block - either the first or the last - plus $Y_{pattern} - Y_{overlap}$ non-overlapping elements in each of the other blocks. Thus,

$$Y_{big} = Y_{pattern} + (Y_{pattern} - Y_{overlap}) * (Y_{small} - 1) \quad (1)$$

Of course, Y_{small} is an integer, so that only certain values of $Y_{pattern}$ and $Y_{overlap}$ can be chosen to preserve the above integer equality. From (1),

$$Y_{small} = 1 + (Y_{big} - Y_{pattern})/(Y_{pattern} - Y_{overlap}) \quad (2)$$

The number of column-wide blocks is given by equation (2). For example, if there are $Y_{big} = 5$ columns in the input pattern matrix, one feasible blocking is the following:

$Y_{pattern} = 3$ elements per block with
$Y_{overlap} = 1$ element overlap, resulting in
$Y_{small} = 2$ column blocks.

All of the above arguments leading to equation (2) apply as well to rows, with the substitution of "rows" for "columns". This derivation leads to

$$X_{small} = 1 + (X_{big} - X_{pattern})/(X_{pattern} - X_{overlap}), \quad (3)$$

where $X_{pattern}$ and $X_{overlap}$ must be chosen to yield an integer X_{small}. Since, there are X_{small} row-wise blocks and Y_{small} column-wise blocks, the total number of middle layer nodes (M) is given by

$$M = X_{small} \times Y_{small}, \quad (4)$$

each middle-layer node being connected to each element in just one block.

To summarize, the formulas used as a guide to the relative dimensions between the big and small layers and the pattern and overlap area include:

$$X_{big} = X_{pattern} + (X_{pattern} - X_{overlap}) * (X_{small} - 1)$$

and

$$Y_{big} = Y_{pattern} + (Y_{pattern} - Y_{overlap}) * (Y_{small} - 1)$$

A.3. General operations of NETS used during studies

Once a network pattern has been created, the NETS program may be operated following these sequence of patterns:

A.3.1. Create.

Select 'c' from the NETS main menu to create a network and enter the following information:

1) Name of file with net configuration.
2) Enter maximum weight value (use default)
3) Enter minimum weight value (use default)
4) Use a global learning rate (answer Yes)
5) Enter global learning rate (use default)
6) Use a global momentum (answer Yes)
7) Enter a global momentum (use default)
8) Use biases in network (answer No)

A.3.2. Initialize.

Select 'i' from the NETS main menu and enter the name of the training file.

A.3.3. Train.

Select 't' from the NETS main menu to train the network. Enter the desired constraint error, the desired number of cycles, and the cycle increment. When the max error value converges to a value less than or equal to the constraint error before completing the desired number of cycles, the network is considered to be trained.

A.3.4. Saving and Restoring weights.

After training the net, it is imperative to save the connections between the nodes because training networks, especially large ones, can often take a lot of time. These connections - called weights - generated by the neural net may be saved into a special types of files. To save the weights, select 's' from the NETS main menu and enter the name of the file. There are two file formats available for use. The first, which ends in .fwt, uses a binary format for a fast save but is unreadable in text format. The second, .pwt, are portable format weight files readable in text format. These two type of files are not compatible with one another. To avoid confusion, NETS labels each of these files such that it can check at run time that the filename specified matches the format desired.

To restore the weights (prior to training a network), select 'r' from the NETS main menu and enter the name of the file. Restoring the weights into a neural net is particularly useful when increasing the number of samples in the training set.

A.3.5. Propagate

Select 'p' from the NETS main menu to filter the input data through the net. Enter the name of the file containing the input data, press return twice, and enter the name of the file containing the results of the propagation. This file is used by the gray scale program to produce a composite picture of the filtered image, which can be visually compared with the clean version of the same image. If the resulting picture is not clear, this same file

can also be used as the input data. The process of generating another image based upon input data previously generated by the net is called recursion. Recursion is useful in enhancing the quality of the image.

A.3.6. Saving source code.

NETS provides an option to generate delivery code of a trained neural network file for portability. To generate computer code select 'g' from the NETS main menu and enter the name of the file to store the code. The generated code will be written in the C programming language.

A.4. Relative and absolute scales of measures.

The absolute scale of measure refers to scaling all images to one scale while the relative scale refers to scaling each image using its own range: $Y_{max} - Y_{min}$. The following equation is used:

$$Y_{ranked} = (Y_{actual} - Y_{min})/(Y_{max} - Y_{min}) * 0.8 + 0.1$$

where Y_{actual} is a numeric value, Y_{max} is the highest value represented by the image and Y_{min} is the lowest value represented by the image. As an example, suppose there are three images that are to be used in a neural network experiment, where each image consists of a certain number of pixels and each pixel is represented by a number. If the absolute scale was to be used, the maximum value would be the highest value found in all three of the images and the minimum value would be the lowest. If relative scale was used, each pixel in each image would be adjusted according to the maximum and minimum values in each image.

Appendix B. NETS architectures used in experiments

These architectures were developed using the following equations:

$$X_{big} = X_{pattern} + (X_{pattern} - X_{overlap})*(X_{small}-1)$$
$$Y_{big} = Y_{pattern} + (Y_{pattern} - Y_{overlap})*(Y_{small}-1)$$

These formulas serve as a guide to calculate the patterned connection scheme between the input and middle layers. The pattern areas refer to the mapping of a group of pixels from one layer onto a single node of another layer. The overlap areas refer to the overlapping of pattern areas with one another, and this overlap may occur in either, or both, the X and Y dimensions. All variables are expressed as integers. All of the input layer, output layer, middle layer, pattern, and overlap dimensions were calculated using this equation.

B.1. 3-sample 500-pixel architectures

These architecture were tested during the development of the 500-pixel architecture using a training file of three samples. All input and output layers represent the noisy and clean images, respectively, and are 500 pixels in size (25 pixels wide by 20 pixels long). All learning times are expressed in seconds:

Using 1 middle layer:
Trained with bias:

	Input	Layer 1	Outer		
Image Size:	25 x 20	5 X 7	25 x 20	Max Error	: 0.197
Block Pattern:	(5,8)			RMS Error	: 0.050
Overlap:	(0,6)			Cycles	: 24
				Learning Time	: 105.0

Trained with and without bias:

	Input	Layer 1	Outer
Image Size:	25 x 20	7 X 5	25 x 20
Block Pattern:	(7,4)		
Overlap:	(4,0)		

	Max Error	RMS Error	Number of Cycles	Learning Times
with bias:	0.182	0.059	23	98.0
without bias:	0.182	0.059	23	142.0

Others used:

	Input	Layer 1	Outer
Image Size:	25 x 20	5 X 7	25 x 20
Block Pattern:	(9,8)		
Overlap:	(5,6)		

Using 2 middle layers:
Trained with bias:

	Input	Layer 1	Layer 2	Outer		
Image Size:	25 x 20	5 x 7	4 x 5	25 x 20	Max Error	: 0.187
Block Pattern:	(5,8)	(2,3)			RMS Error	: 0.060
Overlap:	(0,6)	(1,2)			Cycles	: 90
					Learning Time	: 273.0

	Input	Layer 1	Layer 2	Outer		
Image Size:	25 x 20	5 x 7	5 x 5	25 x 20	Max Error	: 0.193
Block Pattern:	(9,8)	(1,3)			RMS Error	: 0.067
Overlap:	(5,6)	(0,2)			Cycles	: 89
					Learning Time	: 334.0

	Input	Layer 1	Layer 2	Outer		
Image Size:	25 x 20	5 x 7	5 x 4	25 x 20	Max Error	: 0.198
Block Pattern:	(5,8)	(3,2)			RMS Error	: 0.066
Overlap:	(0,6)	(2,1)			Cycles	: 95
					Learning Time	: 382.0

	Input	Layer 1	Layer 2	Outer		
Image Size:	25 x 20	5 x 7	5 x 5	25 x 20	Max Error	: 0.198
Block Pattern:	(5,8)	(3,1)			RMS Error	: 0.055
Overlap:	(0,6)	(2,0)			Cycles	: 52
					Learning Time	: 189.0

Trained without bias:

	Input	Layer 1	Layer 2	Outer		
Image Size:	25 x 20	5 x 7	5 x 5	25 x 20	Max Error	: 0.197
Block Pattern:	(5,8)	(1,3)			RMS Error	: 0.058
Overlap:	(0,6)	(0,2)			Cycles	: 49
					Learning Time	: 149.0

	Input	Layer 1	Layer 2	Outer		
Image Size:	25 x 20	5 x 7	4 x 4	25 x 20	Max Error	: 0.197
Block Pattern:	(5,8)	(2,4)			RMS Error	: 0.051
Overlap:	(0,6)	(1,3)			Cycles	: 45
					Learning Time	: 118.0

	Input	Layer 1	Layer 2	Outer		
Image Size:	25 x 20	5 x 7	4 x 5	25 x 20	Max Error	: 0.199
Block Pattern:	(5,8)	(2,3)			RMS Error	: 0.044
Overlap:	(0,6)	(1,2)			Cycles	: 81
					Learning Time	: 222.0

	Input	Layer 1	Layer 2	Outer		
Image Size:	25 x 20	5 x 7	4 x 5	25 x 20	Max Error	: 0.196
Block Pattern:	(9,8)	(2,3)			RMS Error	: 0.065
Overlap:	(5,6)	(1,2)			Cycles	: 65
					Learning Time	: 208.0

	Input	Layer 1	Layer 2	Outer		
Image Size:	25 x 20	7 x 5	5 x 4	25 x 20	Max Error	: 0.188
Block Pattern:	(7,4)	(3,2)			RMS Error	: 0.077
Overlap:	(4,0)	(2,1)			Cycles	: 43
					Learning Time	: 133.0

	Input	Layer 1	Layer 2	Outer		
Image Size:	25 x 20	7 x 5	5 x 5	25 x 20	Max Error	: 0.199
Block Pattern:	(7,4)	(3,1)			RMS Error	: 0.063
Overlap:	(4,0)	(2,0)			Cycles	: 30
					Learning Time	: 110.0

Trained without biases (continued):

	Input	Layer 1	Layer 2	Outer	
Image Size:	25 x 20	7 x 5	4 x 4	25 x 20	Max Error : 0.195
Block Pattern:	(7,4)	(4,2)			RMS Error : 0.060
Overlap:	(4,0)	(3,1)			Cycles : 34
					Learning Time: 89.0

Trained with and without bias:

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 7	5 x 4	25 x 20
Block Pattern:	(5,8)	(1,4)		
Overlap:	(0,6)	(0,3)		

	Max Error	RMS Error	Number of Cycles	Learning Times
with bias:	0.195	0.052	44	155.0
without bias:	0.182	0.059	46	164.0

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 7	5 x 4	25 x 20
Block Pattern:	(9,8)	(1,4)		
Overlap:	(5,6)	(0,3)		

	Max Error	RMS Error	Number of Cycles	Learning Times
with bias:	0.190	0.088	86	275.0
without bias:	0.199	0.044	81	222.0

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 7	4 x 4	25 x 20
Block Pattern:	(9,8)	(2,4)		
Overlap:	(5,6)	(1,3)		

	Max Error	RMS Error	Number of Cycles	Learning Times
with bias:	0.198	0.073	98	277.0
without bias:	0.192	0.060	64	181.0

Others:

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	7 x 5	4 x 5	25 x 20
Block Pattern:	(7,4)	(4,1)		
Overlap:	(4,0)	(3,0)		

Using 3 middle layers (none successfully converged):

	Input	Layer 1	Layer 2	Layer 3	Outer
Image Size:	25 x 20	5 x 7	5 x 4	2 x 2	25 x 20
Block Pattern:	(5,8)	(1,4)	(3,2)		
Overlap:	(0,6)	(0,3)	(1,0)		

Using 3 middle layers (continued):

	Input	Layer 1	Layer 2	Layer 3	Outer
Image Size:	25 x 20	5 x 7	5 x 5	2 x 2	25 x 20
Block Pattern:	(5,8)	(1,3)	(3,3)		
Overlap:	(0,6)	(0,2)	(1,0)		

	Input	Layer 1	Layer 2	Layer 3	Outer
Image Size:	25 x 20	5 x 7	4 x 4	2 x 2	25 x 20
Block Pattern:	(5,8)	(2,4)	(2,2)		
Overlap:	(0,6)	(1,3)	(0,0)		

	Input	Layer 1	Layer 2	Layer 3	Outer
Image Size:	25 x 20	5 x 7	4 x 5	2 x 2	25 x 20
Block Pattern:	(5,8)	(2,3)	(2,3)		
Overlap:	(0,6)	(1,2)	(0,1)		

	Input	Layer 1	Layer 2	Layer 3	Outer
Image Size:	25 x 20	5 x 7	5 x 4	2 x 2	25 x 20
Block Pattern:	(9,8)	(1,4)	(3,2)		
Overlap:	(5,6)	(0,3)	(1,0)		

	Input	Layer 1	Layer 2	Layer 3	Outer
Image Size:	25 x 20	5 x 7	5 x 5	2 x 2	25 x 20
Block Pattern:	(9,8)	(1,3)	(3,3)		
Overlap:	(5,6)	(0,2)	(1,1)		

	Input	Layer 1	Layer 2	Layer 3	Outer
Image Size:	25 x 20	5 x 7	4 x 4	2 x 2	25 x 20
Block Pattern:	(9,8)	(2,4)	(2,2)		
Overlap:	(5,6)	(1,3)	(0,0)		

	Input	Layer 1	Layer 2	Layer 3	Outer
Image Size:	25 x 20	5 x 7	4 x 5	2 x 2	25 x 20
Block Pattern:	(9,8)	(2,3)	(2,3)		
Overlap:	(5,6)	(1,2)	(0,1)		

	Input	Layer 1	Layer 2	Layer 3	Outer
Image Size:	25 x 20	7 x 5	5 x 4	2 x 2	25 x 20
Block Pattern:	(7,4)	(3,2)	(3,2)		
Overlap:	(4,0)	(2,1)	(1,0)		

	Input	Layer 1	Layer 2	Layer 3	Outer
Image Size:	25 x 20	7 x 5	5 x 5	2 x 2	25 x 20
Block Pattern:	(7,4)	(3,1)	(3,3)		
Overlap:	(4,0)	(2,0)	(1,1)		

	Input	Layer 1	Layer 2	Layer 3	Outer
Image Size:	25 x 20	7 x 5	4 x 4	2 x 2	25 x 20
Block Pattern:	(7,4)	(4,2)	(2,2)		
Overlap:	(4,0)	(3,1)	(0,0)		

Using 3 middle layers (continued):

	Input	Layer 1	Layer 2	Layer 3	Outer
Image Size:	25 x 20	7 x 5	4 x 5	2 x 2	25 x 20
Block Pattern:	(7,4)	(4,1)	(2,3)		
Overlap:	(4,0)	(3,0)	(0,1)		

8.2. 5-sample 500-pixel architectures

These architectures were tested during the development of the 500-pixel architecture using a training file of five samples. All input and output layers represent the noisy and clean images, respectively, and are 500 pixels in size (25 pixels wide by 20 pixels long):

Using 1 middle layer:

Trained with biases:

	Input	Layer 1	Outer		
Image Size:	25 x 20	5 X 9	25 x 20	Max Error	: 0.180
Block Pattern:	(9,4)			RMS Error	: 0.054
Overlap:	(5,2)			Cycles	: 38
				Learning Time	: 330.0
	Input	Layer 1	Outer	Max Error	: 0.188
Image Size:	25 x 20	5 X 10	25 x 20	RMS Error	: 0.043
Block Pattern:	(5,2)			Cycles	: 176
Overlap:	(0,0)			Learning Time	: 695.0
	Input	Layer 1	Outer	Max Error	: 0.175
Image Size:	25 x 20	5 X 10	25 x 20	RMS Error	: 0.062
Block Pattern:	(9,2)			Cycles	: 130
Overlap:	(5,0)			Learning Time	: 296.0
	Input	Layer 1	Outer	Max Error	: 0.196
Image Size:	25 x 20	10 X 5	25 x 20	RMS Error	: 0.048
Block Pattern:	(7,4)			Cycles	: 43
Overlap:	(5,0)			Learning Time	: 407.0

Trained without biases:

	Input	Layer 1	Outer		
Image Size:	25 x 20	5 X 9	25 x 20	Max Error	: 0.100
Block Pattern:	(5,4)			RMS Error	: 0.039
Overlap:	(0,2)			Cycles	: 132
				Learning Time	: 1043.0

Using 2 middle layers (none successfully converged):

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 9	4 x 4	25 x 20
Block Pattern:	(5,4)	(2,3)		
Overlap:	(0,2)	(1,1)		
	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 9	4 x 4	25 x 20
Block Pattern:	(5,4)	(5,3)		
Overlap:	(0,2)	(5,1)		

Using 2 middle layers (continued):

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 9	4 x 5	25 x 20
Block Pattern:	(5,4)	(2,5)		
Overlap:	(0,2)	(1,4)		

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 9	4 x 5	25 x 20
Block Pattern:	(5,4)	(5,5)		
Overlap:	(0,2)	(5,4)		

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 9	5 x 5	25 x 20
Block Pattern:	(5,4)	(1,3)		
Overlap:	(0,2)	(0,1)		

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 9	5 x 5	25 x 20
Block Pattern:	(5,4)	(5,3)		
Overlap:	(0,2)	(5,1)		

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 9	5 x 6	25 x 20
Block Pattern:	(5,4)	(1,5)		
Overlap:	(0,2)	(0,4)		

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 9	5 x 6	25 x 20
Block Pattern:	(5,4)	(5,4)		
Overlap:	(0,2)	(5,5)		

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 9	4 x 4	25 x 20
Block Pattern:	(9,4)	(2,3)		
Overlap:	(5,2)	(1,1)		

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 9	4 x 5	25 x 20
Block Pattern:	(9,4)	(2,5)		
Overlap:	(5,2)	(1,4)		

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 9	5 x 5	25 x 20
Block Pattern:	(9,4)	(1,3)		
Overlap:	(5,2)	(0,1)		

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 9	5 x 6	25 x 20
Block Pattern:	(9,4)	(1,5)		
Overlap:	(5,2)	(4,0)		

Using 2 middle layers (continued):

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 10	4 x 4	25 x 20
Block Pattern:	(5,2)	(2,3)		
Overlap:	(0,0)	(1,1)		

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 10	4 x 5	25 x 20
Block Pattern:	(5,2)	(2,5)		
Overlap:	(0,0)	(1,4)		

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 10	5 x 4	25 x 20
Block Pattern:	(5,2)	(1,4)		
Overlap:	(0,0)	(0,2)		

	Input	Layer 1	Layer 2	Outer
Image Size:	25 x 20	5 x 10	5 x 5	25 x 20
Block Pattern:	(5,2)	(1,5)		
Overlap:	(0,0)	(0,4)		

Appendix C: Summary of Experimental Results

C.1. Terminology.

For the tables below, each column heading is abbreviated using the following symbols:

Sets (S):
- a - clean
- b - propagated
- c - 1st recursion
- d - 2nd recursion

Size of Samples:
- 300 - 300 pixels
- 400 - 400 pixels
- 500 - 500 pixels
- 600 - 600 pixels

Orientation of hole (O):
- L - Slant Left
- S - Straight
- R - Slant Right
- N - Not determinable

Location of Center (L):
- T - Top
- C - Center
- B - Bottom

Shape (S):
- O - Oval
- RO - Roughly Oval
- A - Amoebic (no shape)
- HO - Half-oval
- X - X-shaped

FSR - Fraction of Squared Residual
(t) - Part of training set
(nt) - Not part of training set

The actual values should look like this:

Set	O	L	S	Set	O	L	S	Set	O	L	S	Set	O	L	S
1	L	C	O	7	S	C	O	12	L	C	O	17	R	C	O
2	R	C	O	8	R	C	O	13	S	C	O	18	L	B	HO
3	L	C	O	9	L	C	O	14	R	C	O	19	S	B	HO
5	S	C	O	10	S	C	O	15	L	C	O	20	R	B	HO
6	L	C	O	11	R	C	O	16	S	C	O				

These symbols are used to describe the appearance of the image as generated through the grey-scale program. As an example, set 1 describes an image that is oriented toward the left, where the center of the image is located in the center of the picture, and is oval in shape. To determine whether a generated image represents the clean image, the symbols between the clean and propagated image must match. If the propagated image matches the clean image according to the criteria listed above, and the FSR value is less than 0.25, then the net filtered enough noise to produce the shape of the image.

The charts below summarizes the results of the experiments. The FSR values that are next to the description of the clean image represent the value generated comparing the noisy with the clean image.

	300				400				500				600			
Set	O	L	S	FSR	O	L	S	FSR	O	L	S	FSR	O	L	S	FSR
		(nt)					(nt)				(nt)				(nt)	
1a	L	C	O	.9155	L	C	O	.9151	L	C	O	.9151	L	C	O	.9453
b	L	C	O	.1547	S	C	O	.6340	L	C	O	.1771	L	C	RO	.3227
c	L	C	O	.1259	SL	C	O	.4250	L	C	RO	.2002	L	C	O	.2358
d	-	-	-	----	L	C	O	.2945	L	C	RO	.2031	-	-	-	----
		(nt)					(nt)				(nt)				(nt)	
2a	R	C	O	.4752	R	C	O	.4856	R	C	O	.4856	R	C	O	.5092
b	LSR	C	AX	.2052	SR	C	RO	.3262	R	C	RO	.1419	L	C	RO	.9329
c	SR	C	A	.1259	SR	C	ARO	.3258	R	C	O	.0574	L	C	RO	1.2734
d	-	-	-	----	S	C	A	.3499	R	C	O	.0407	-	-	-	----
		(t)					(t)				(nt)				(t)	
3a	L	C	O	.4297	L	C	O	.4693	L	C	O	.4693	L	C	O	.4737
b	L	C	O	.0117	S	C	O	.2225	L	C	O	.0673	L	C	O	.0137
c	L	C	O	.0232	L	C	O	.1803	L	C	O	.1118	L	C	O	.1900
d	-	-	-	----	L	C	O	.1901	L	C	RO	.1142	-	-	-	----
		(t)					(t)				(t)				(t)	
5a	S	C	O	.5510	S	C	O	.7000	S	C	O	2.595	S	C	O	.6319
b	S	C	O	.0112	S	C	O	.1699	S	C	RO	.0126	S	C	O	.0192
c	S	C	AX	.0941	LS	C	ARO	----	LS	C	RO	.1450	S	CB	RO	.2400
d	-	-	-	----	L	C	O	----	L	C	RO	.3529	-	-	-	----
		(t)					(t)				(t)				(t)	
6a	L	C	O	.5505	L	C	O	.6237	L	C	O	.6237	L	C	O	.6540
b	L	C	O	.0111	L	C	O	.1614	L	C	O	.0123	L	C	O	.0219
c	L	C	O	.0213	L	C	O	----	L	C	RO	.0986	L	C	O	.0657
d	-	-	-	----	L	C	O	----	L	C	RO	.1386	-	-	-	----
		(t)					(t)				(t)				(t)	
7a	S	C	O	.5175	S	C	O	.5422	S	C	O	.5422	S	C	O	.5540
b	S	C	O	.0426	S	C	O	.2075	S	C	O	.0258	S	C	O	.0238
c	S	C	OX	.1204	S	C	RO	----	S	C	O	.0339	S	C	RO	.1104
d	-	-	-	----	R	C	O	----	S	C	O	.0454	-	-	-	----
		(t)					(t)				(t)				(t)	
8a	R	C	O	.5491	R	C	O	.5860	R	C	O	.5860	R	C	O	.6266
b	R	C	O	.0110	R	C	O	.1598	R	C	O	.0138	R	C	O	.0183
c	R	C	O	.0189	RS	C	RO	----	R	C	O	.0228	R	C	O	.0626
d	-	-	-	----	S	C	RO	----	R	C	O	.0261	-	-	-	----
		(nt)					(t)				(t)				(nt)	
9a	L	C	O	.5725	L	C	O	.6028	L	C	O	.6028	L	C	O	.6086
b	L	C	O	.0491	L	C	O	.1531	L	C	O	.0104	L	C	A	.4419
c	L	C	O	.0373	L	C	O	----	L	C	RO	.0651	L	C	O	.4481
d	-	-	-	----	L	C	O	----	L	C	RO	.1120	-	-	-	----

	300				400				500				600			
Set	O	L	S	FSR	O	L	S	FSR	O	L	S	FSR	O	L	S	FSR
		(t)					(nt)				(t)				(t)	
10a	S	C	O	.6076	S	C	O	.8010	S	C	O	.8010	S	C	O	1.6056
b	S	C	O	.0132	S	CB	O	.3096	S	C	O	.2131	S	C	O	1.6329
c	S	C	XA	.1126	S	C	RO	.1784	S	C	O	.2249	S	C	RO	1.4910
d	-	-	-	----	SL	C	RO	.1991	S	C	O	.3590	-	-	-	----
		(nt)					(nt)				(t)				(t)	
11a	R	C	O	.6475	R	C	O	.7834	R	C	O	.7834	R	C	O	.6961
b	S	C	XA	.2215	R	C	RO	.2488	S	C	O	.2031	R	C	O	.0123
c	S	C	XRO	.1580	S	C	RO	.4075	R	C	O	.2136	R	C	A	.4266
d	-	-	-	----	S	C	RO	.4798	R	C	O	.2175	-	-	-	----
		(nt)					(t)				(t)				(t)	
12a	L	C	O	.5266	L	C	O	.6433	L	C	O	.6433	L	C	O	.6913
b	S	C	XA	.3873	L	C	O	.1507	L	C	O	.0115	L	C	O	.0206
c	SR	C	A	.4930	L	C	O	----	L	C	RO	.0773	L	C	O	.0826
d	-	-	-	----	L	C	O	----	L	C	RO	.1335	-	-	-	----
		(t)					(nt)				(t)				(nt)	
13a	S	C	O	.6285	S	C	O	.7536	S	C	O	.6805	S	C	O	.6722
b	S	C	O	.0127	S	C	RO	.2870	S	C	O	.0124	L	C	O	.8043
c	S	C	ROX	.1125	L	C	RO	.4512	S	C	O	.0218	L	C	O	.7611
d	-	-	-	----	L	C	O	.6146	S	C	O	.0223	-	-	-	----
		(nt)					(nt)				(nt)				(nt)	
14a	R	C	O	.4597	L	C	O	.6461	R	C	O	1.672	R	C	O	.6002
b	R	C	O	.0109	LS	C	RO	.3341	R	C	O	.0121	L	C	O	1.293
c	R	C	O	.0227	SR	C	RO	.3683	R	C	O	.0260	L	C	O	1.349
d	-	-	-	----	SR	C	RO	.3540	R	C	O	.0331	-	-	-	----
		(t)					(nt)				(nt)				(t)	
15a	L	C	O	.5718	L	C	O	.6496	L	C	O	.6576	L	C	O	.6748
b	L	C	O	.0112	L	CB	ROX	.4527	S	C	RO	.2885	L	C	O	.0139
c	L	C	O	.0457	L	C	RO	.2941	L	C	RO	.1192	L	C	O	.3910
d	-	-	-	----	L	C	RO	.1640	L	C	RO	.1190	-	-	-	----
		(nt)					(t)				(nt)				(nt)	
16a	S	C	O	.6325	S	C	O	.7044	S	C	O	.7044	S	C	O	.7151
b	S	C	RO	.0521	S	C	O	.1685	S	C	O	.0564	L	C	O	.4046
c	S	C	AX	.1393	SL	C	RO	----	S	C	O	.0319	L	C	O	.7339
d	-	-	-	----	L	C	RO	----	S	C	O	.0237	-	-	-	----
		(nt)					(t)				(nt)				(nt)	
17a	R	C	O	.4644	R	C	O	.5164	R	C	O	.5164	R	C	O	.5465
b	S	C	XA	.3970	R	C	O	.1563	S	C	RO	.3073	R	C	A	.8610
c	S	C	XA	.2807	RS	C	RO	----	R	C	O	.1192	L	C	A	1.034
d	-	-	-	----	RS	C	RO	----	R	C	O	.0577	-	-	-	----

	300				400				500				600			
Set	O	L (nt)	S	FSR	O	L	S (t)	FSR	O	L	S (nt)	FSR	O	L	S (t)	FSR
18a	L	B	HO	.8044	L	B	HO	.7808	L	B	HO	.7808	L	B	HO	.8213
b	L	B	HO	.0171	L	B	HO	.3569	S	C	O	.9996	L	B	HO	.2990
c	S	B	RO	.2075	L	B	RHO	.4992	S	C	RO	.9871	M	BC	A	.4133
d	-	-	-	----	S	B	RO	.5921	L	C	RO	1.04	-	-	-	----
		(nt)					(t)				(nt)				(nt)	
19a	S	B	HO	.8623	S	B	HO	.8003	S	C	HO	.8003	S	B	HO	.8497
b	L	C	O	.3816	S	B	HO	.3337	S	C	RO	.5749	M	C	A	1.173
c	L	C	O	.4435	L	BC	RO	.6148	L	ULC	O	.6418	S	C	RO	1.175
d	-	-	-	----	L	C	O	.7868	L	ULC	O	.6930	-	-	-	----
		(nt)					(nt)				(nt)				(nt)	
20a	R	B	H	1.140	R	B	HO	1.028	R	B	HO	2.326	R	B	HO	.4286
b	S	C	ROX	1.557	S	BC	ARO	1.076	S	C	RO	1.353	L	C	RO	1.092
c	S	C	ROX	1.685	S	C	RO	1.381	S	LC	O	1.361	L	C	O	1.636
d	-	-	-	----	LS	C	RO	1.387	S	LC	O	1.414	-	-	-	----

C.2. Summary of samples in the training set

Based upon the shape, orientation, and location of the the center of the clean image, the net filtered enough noise to produce an image similar to the clean image after one propagation. With a few exceptions, only one propagation was required.

C.2.1. Chart of results from training set

The following chart represents the number of propagations required for the net to filter enough noise to produce an image. 1 represents one propagation, 2 represents one propagation and one recursion, and NA means that the data file was not part of the training set. There are ten samples in each of the data sets.

Set	300	400	500	600	Set	300	400	500	600
3	1	2	NA	1	12	NA	1	1	1
5	1	1	~1	1	13	1	NA	1	NA
6	1	1,2	1	1	14	1	NA	1	NA
7	1	1	1	1	15	1	NA	NA	1
8	1	1	1	1	16	NA	1	NA	NA
9	NA	1	1	NA	17	NA	1	NA	NA
10	1	NA	1,2	1	18	1	~1	NA	1
11	NA	NA	2	1	19	NA	1	NA	NA

C.2.2. Conclusions from the test data:

With few exceptions, the size of examples within the training sets does not matter when filtering noisy data from input that is part of the training set. Only one propagation is required. Recursion may be used only if the net had trouble filtering noise. In such a case one recursion operation should be used or else the net will never be able to filter noise to produce a clean image.

C.3. Summary of non-training sets

Based upon the shape, orientation, and location of the the center of the clean image, the net filtered enough noise to produce an image similar to the clean image after one or two propagations. For many cases recursion made a difference, for others that did not matter. The net had trouble filtering those images whose center appeared at the bottom of the page and is half-oval (truncated ellipse) in shape.

C.3.1. Chart of results from training set

The following chart represents the number of propagations required for the net to filter enough noise to produce an image. 1 represents one propagation, 2 represents one propagation and one recursion, 3 represents one propagation and two recursions, NA means that the data file was not part of the training set, and No means that not enough noise was filtered to produce an acceptable image. Altogether there are nine samples in each of the data sets.

Set	300	400	500	600	Set	300	400	500	600
1	1,2	3	~1	2	14	NA	No	NA	No
2	No	No	2,3	No	15	NA	3	2,3	NA
3	NA	NA	1	NA	16	1	%A	1,2,3	No
9	1,2	NA	NA	No	17	No	NA	c	No
10	NA	2	NA	NA	18	NA	NA	No	NA
11	No	~1	NA	NA	19	No	NA	No	No
12	No	NA	NA	NA	20	No	No	No	No
13	NA	~1	NA	No					

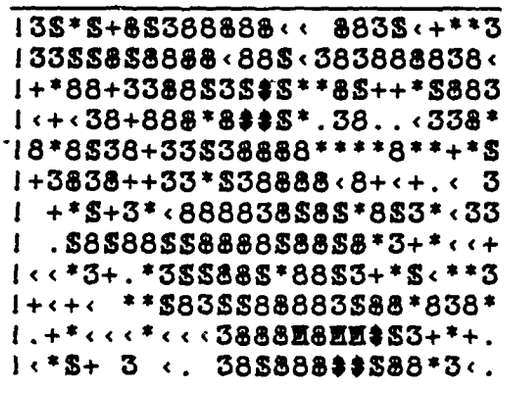
C.3.2. Conclusions from the non-training data:

Sets 18, 19, and 20 represent only a partial image, while the reminder of the sets represent a complete image. None of these partial images were successfully filtered by the net. Recursion works best with non-training sets, where one or two times at most is enough to perform the task. Of all the sample sizes used, 500-pixel network architectures provide the best overall result to filter noise from data to produce a cleaner image; this is followed by 400 pixels. The 300- and 600-pixel size images should be avoided in filtering operations.

C.4. Pictures of Images

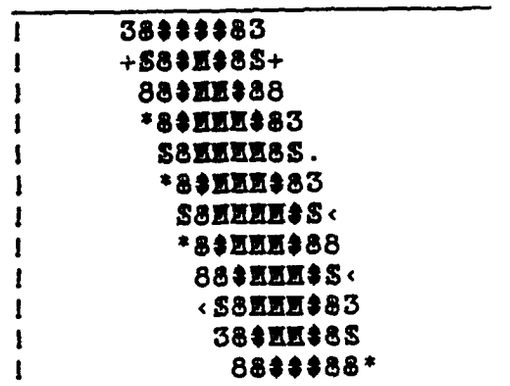
SET 1 - 300nodes
NON-TRAINING SET

C.4.1. 300-pixel images

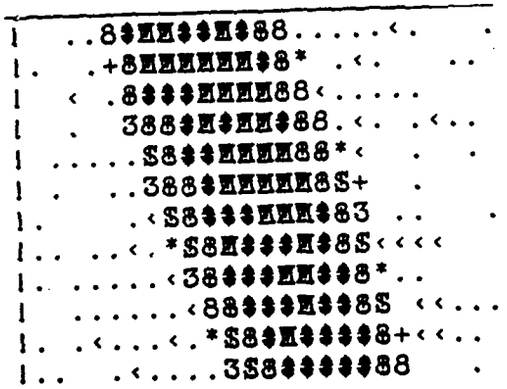


NOISE

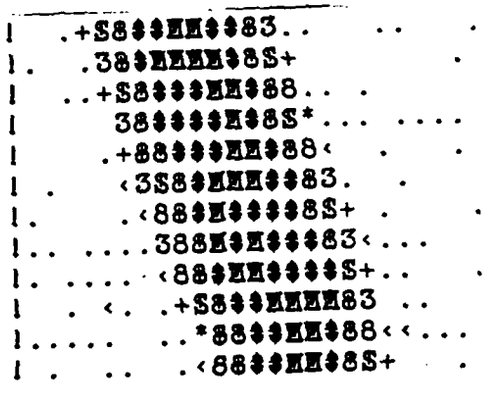
FSR=0.9155



NOISE-FREE



PROPAGATED



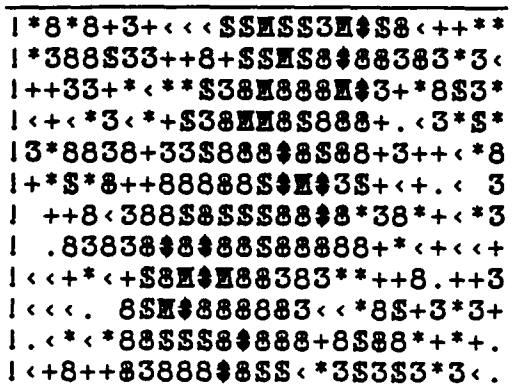
RECURSION

FSR_p=0.1547

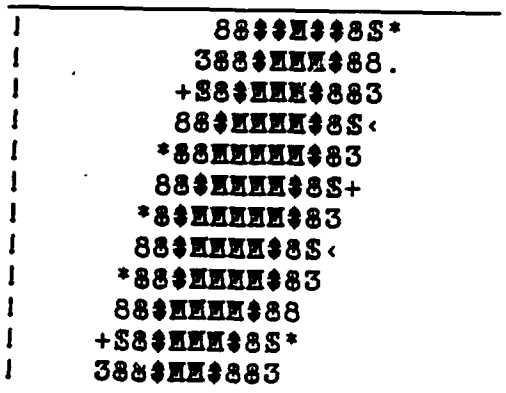
FSR_r=0.1259

StdD=0.3059

SET 2 - 300 pixel
NON-TRAINING

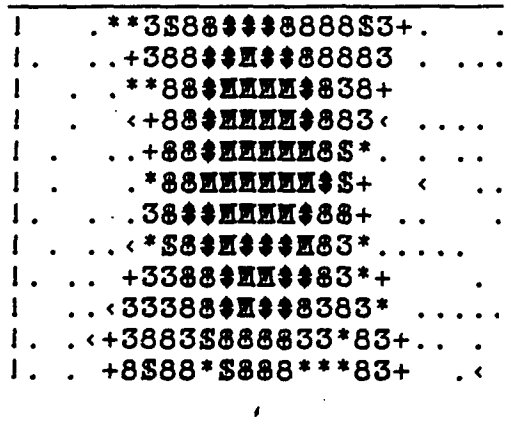


NOISE

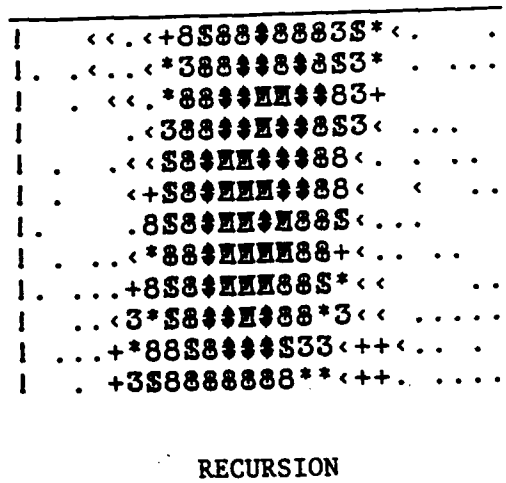


CLEAN

FSR = 0.4752



PROPAGATED

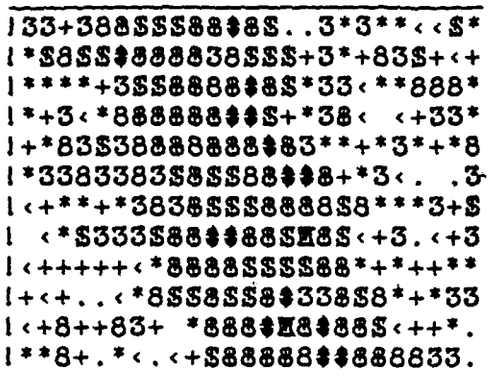


RECURSION

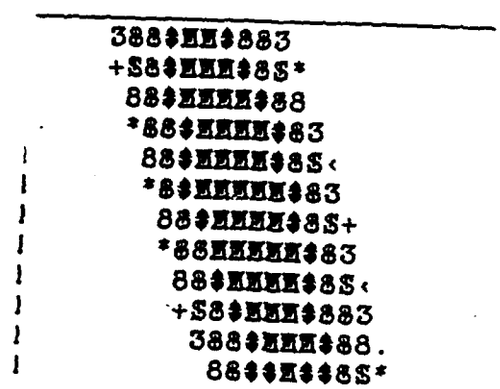
FSR_p = 0.2052

FSR_r = 0.1265

StdD= 0.3245

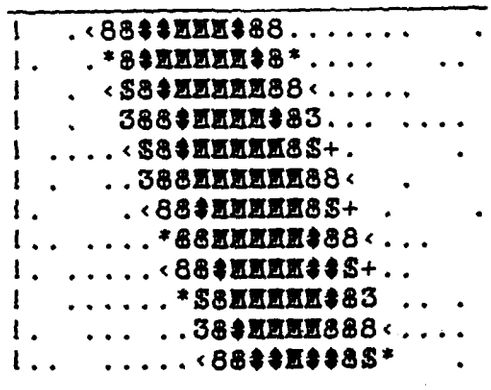


NOISE

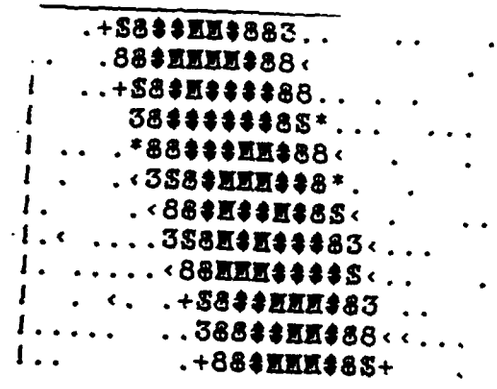


CLEAN

FSR= 0.4297



PROPAGATED



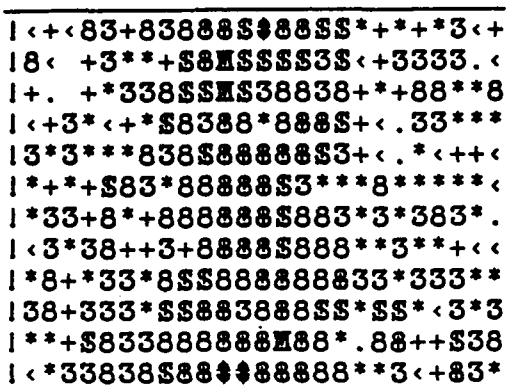
RECURSION

FSR_p= 0.0117

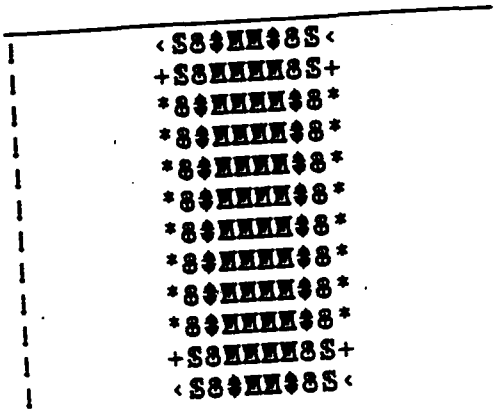
FSR_r= 0.0232

StdD= 0.3245

SET 5 - 300 pixel
TRAINING

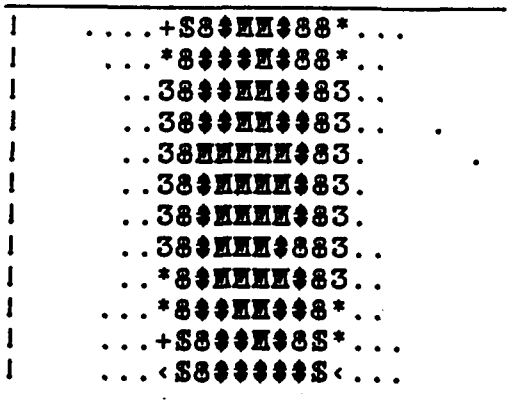


NOISE

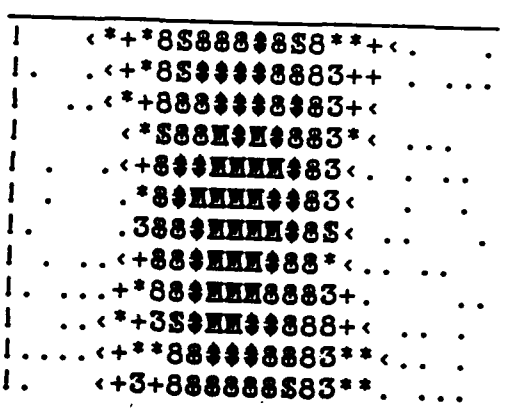


CLEAN

FSR= 0.5510



PROPAGATED



RECURSION

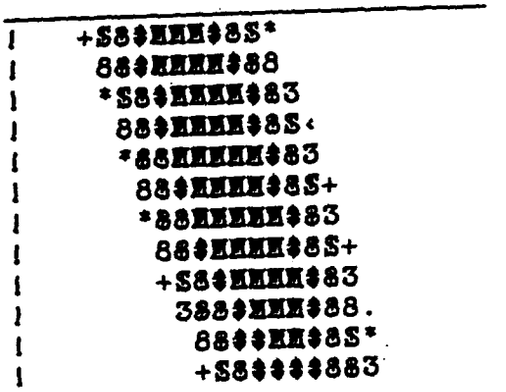
FSR_p= 0.0112

FSR_r= 0.0941

StdD= 0.3183

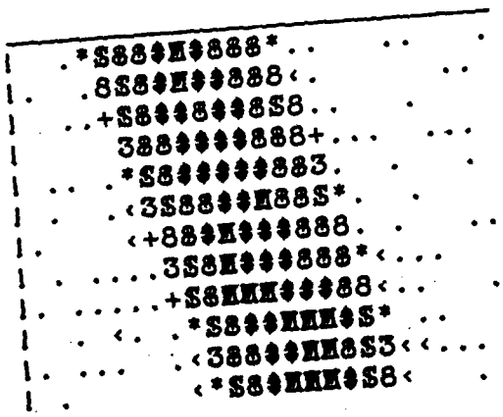
SET 6 - 300 pixel
TRAINING

NOISE

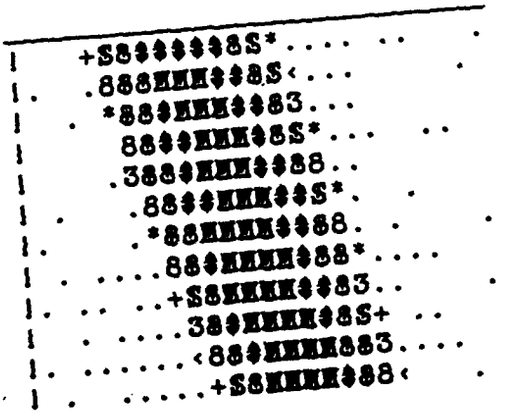


CLEAN

FSR= 0.5505



PROPAGATED



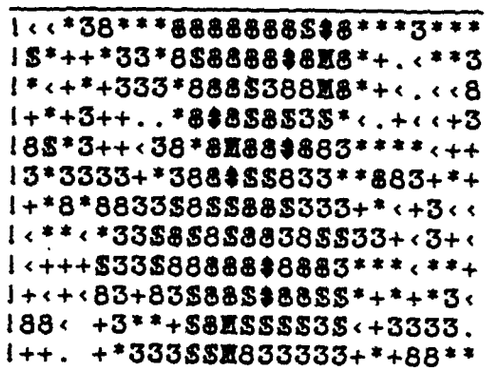
RECURSION

FSR_p= 0.0111

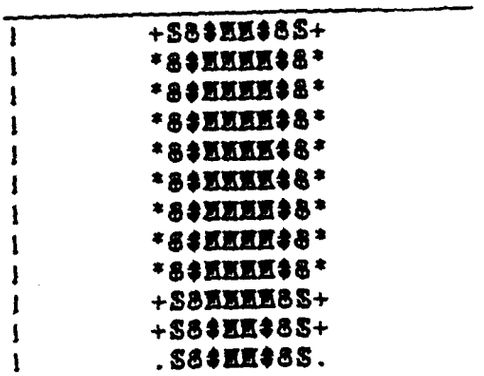
FSR_r= 0.0213

StdD= 0.3241

SET 7 - 300 pixel
TRAINING

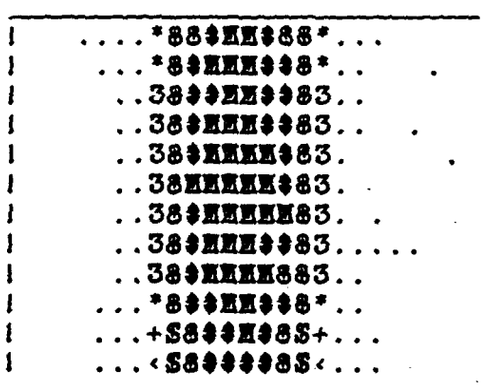


NOISE

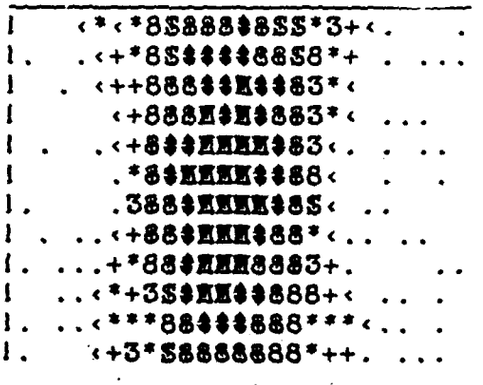


CLEAN

FSR= 0.5175



PROPAGATED



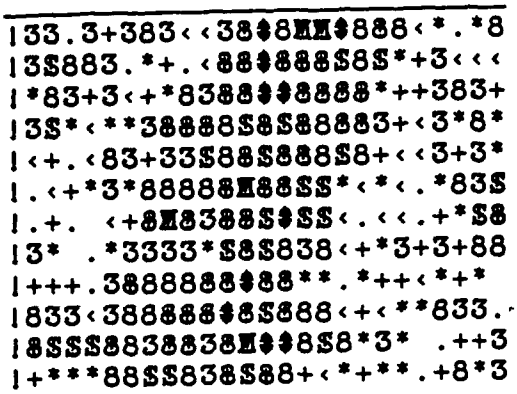
RECURSION

FSR_p= 0.0426

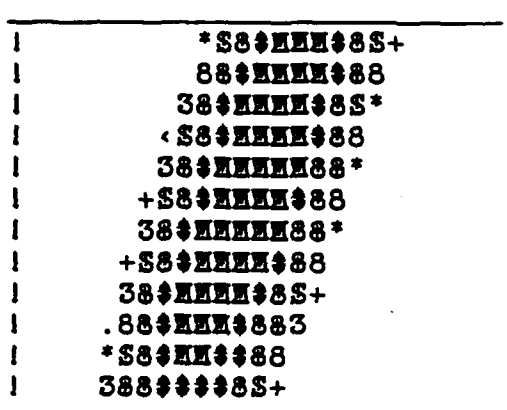
FSR_r= 0.1204

StdD= 0.3179

SET 8 - 300 pixel
TRAINING



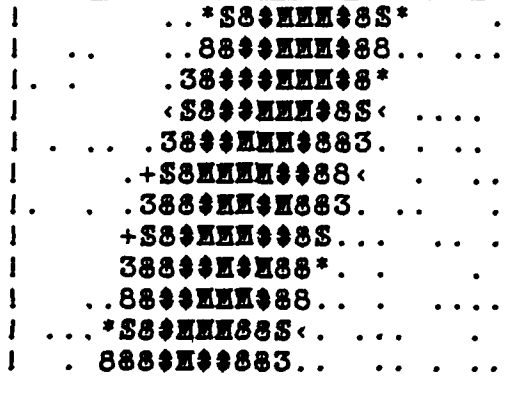
NOISE



CLEAN

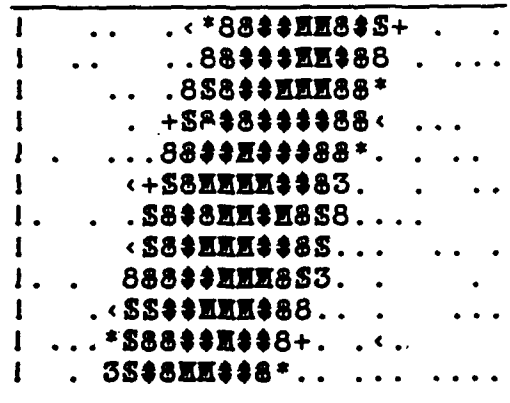
FSR= 0.5491

C



PROPAGATED

FSR_p= 0.0110

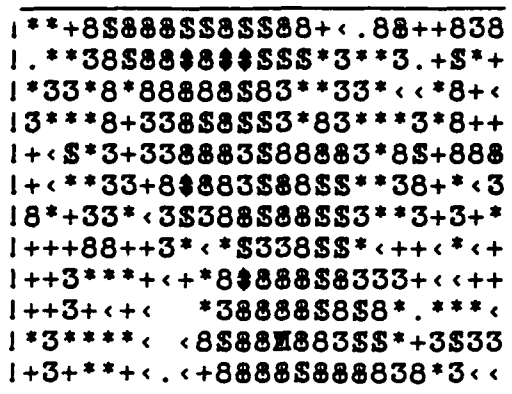


RECURSION

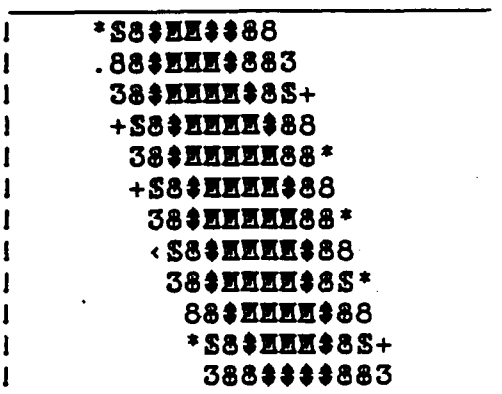
FSR_r= 0.0189

StdD= 0.3241

SET 9 - 300pixel
NON-TRAINING

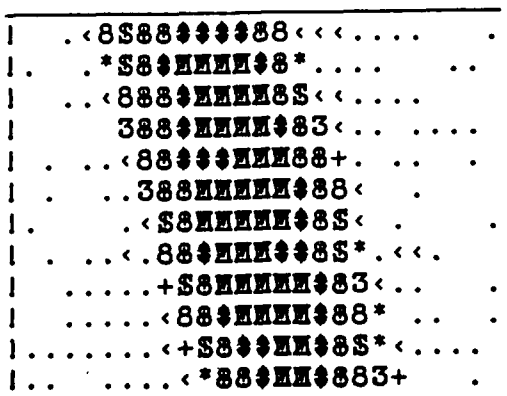


NOISE

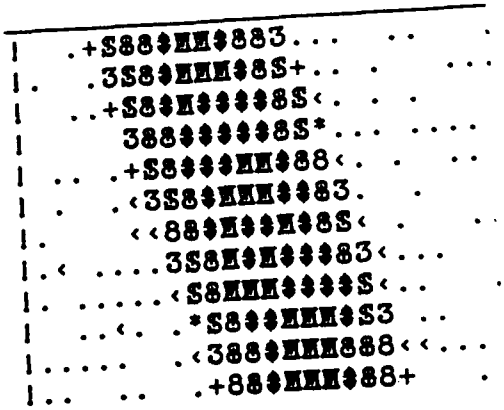


CLEAN

FSR= 0.5725



PROPAGATED



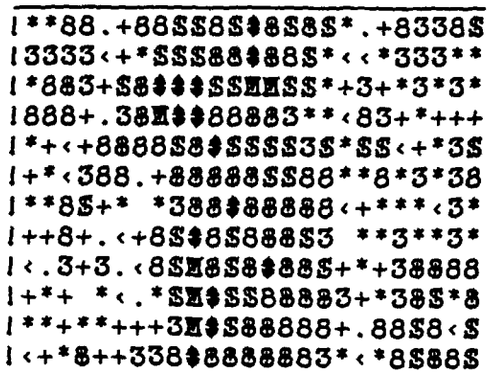
RECURSION

FSR_p= 0.0491

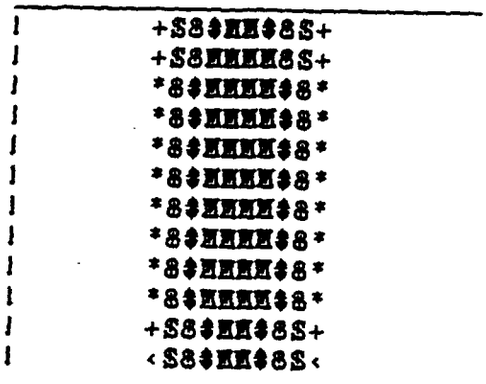
FSR_r= 0.0373

StdD= 0.3246

SET 10 - 300pixel
TRAINING

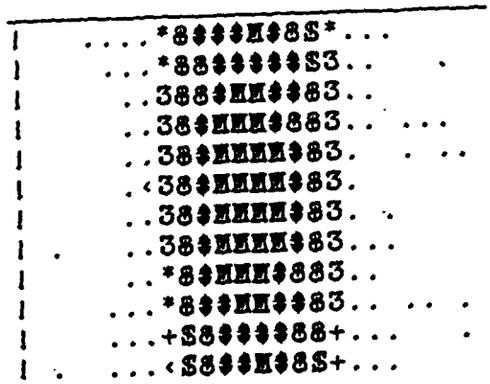


CLEAN

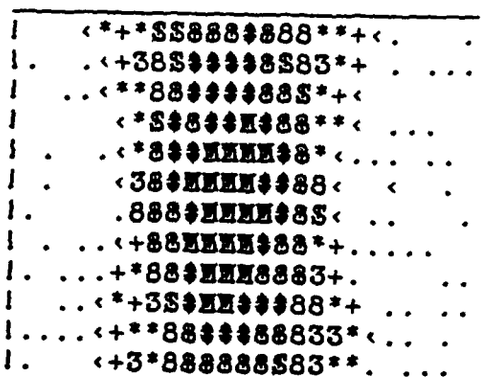


NOISE

FSR= 0.6076



PROPAGATED



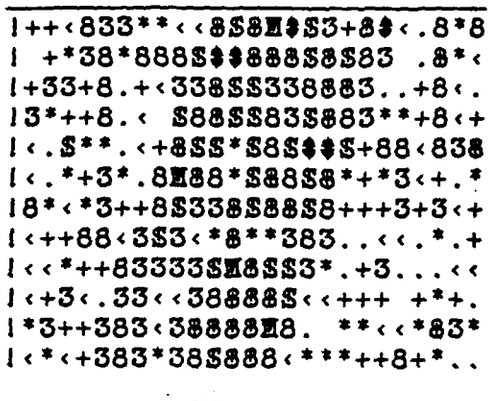
RECURSION

FSR_p= 0.0132

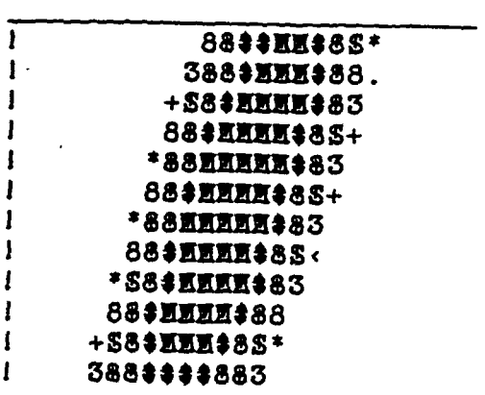
FSR_r= 0.1126

StdD= 0.3182

SET 11 - 300pixel
NON-TRAINING

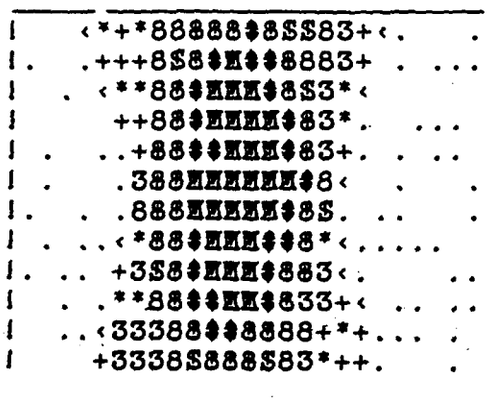


NOISE

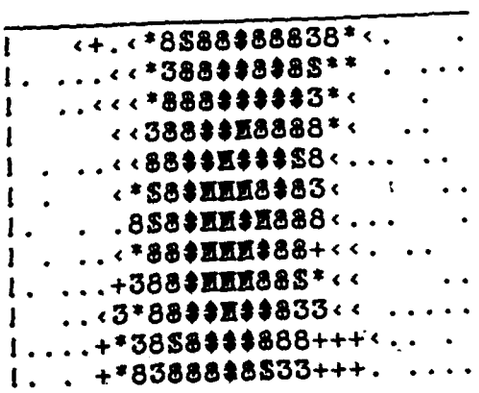


CLEAN

FSR= 0.6475



PROPAGATED



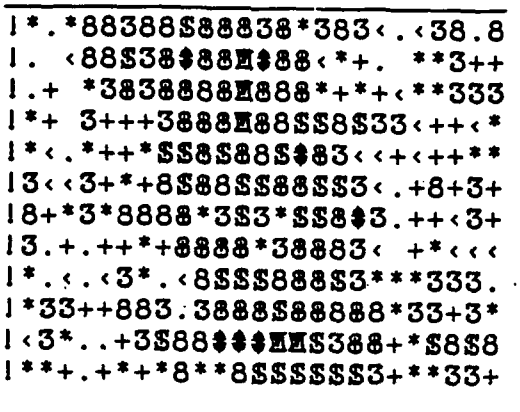
RECURSION

FSR_p= 0.2215

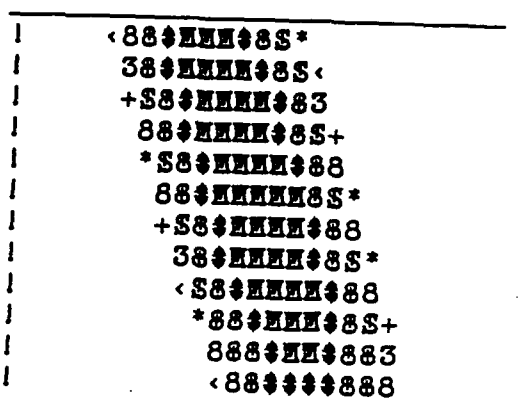
FSR_r= 0.1580

StdD= 0.3246

SET 12 - 300pixel
NON-TRAINING

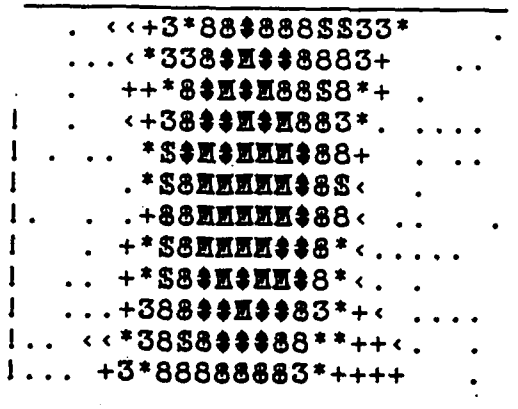


NCISE

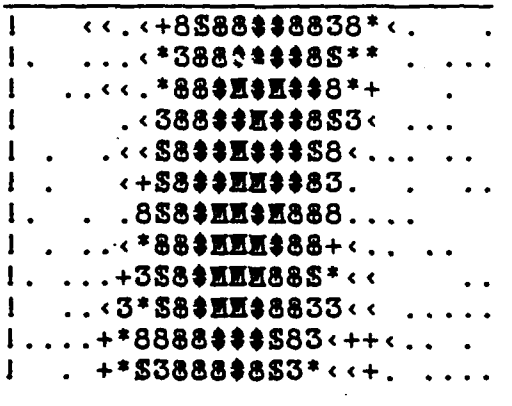


CLEAN

FSR= 0.5226



PROPAGATED



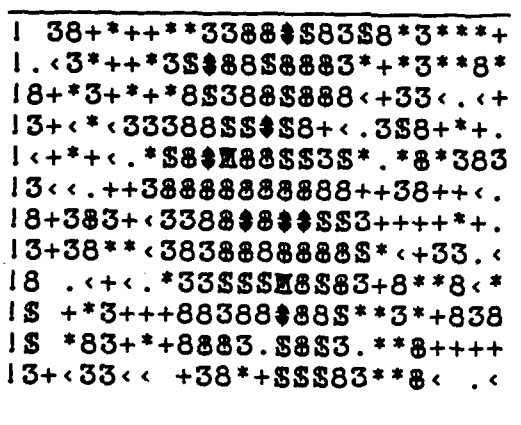
RECURSION

FSR_p= 0.3873

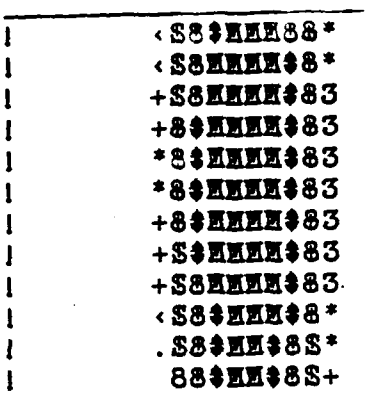
FSR_r= 0.4930

StdD= 0.3176

SET 13 - 300pixel
TRAINING

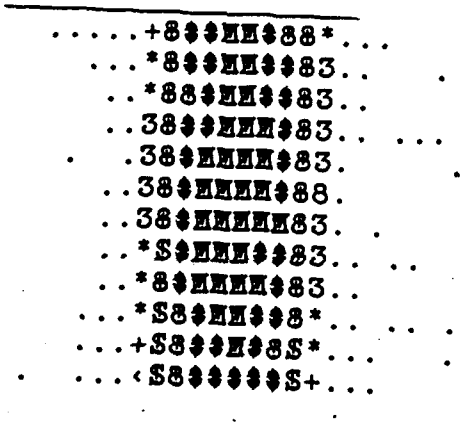


NOISE

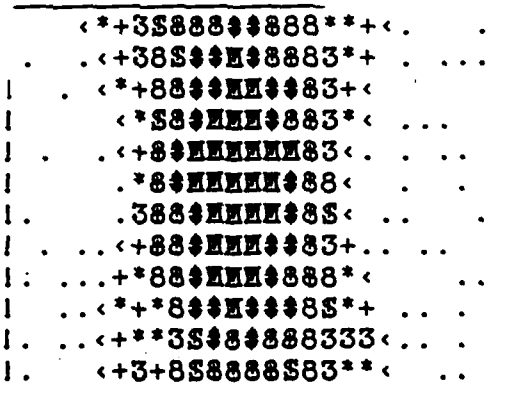


CLEAN

FSR= 0.6285



PROPAGATED



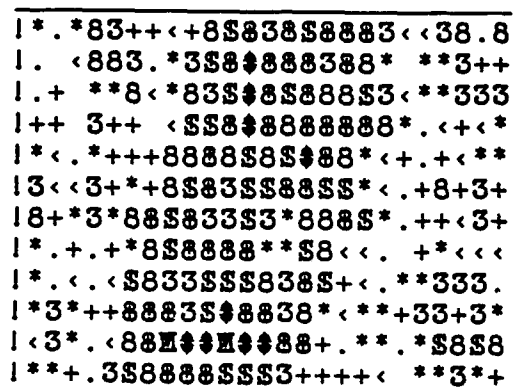
RECURSION

FSR_p= 0.0127

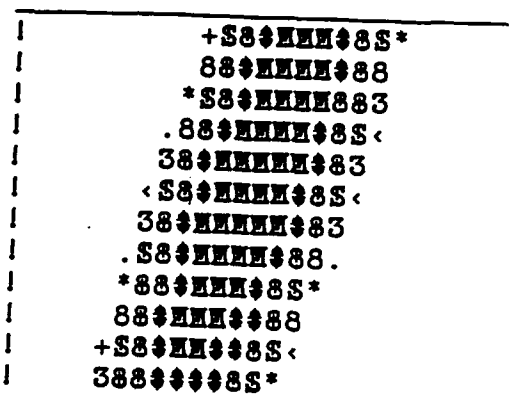
FSR_r= 0.1125

StdD= 0.3176

SET 14 - 300pixel
TRAINING

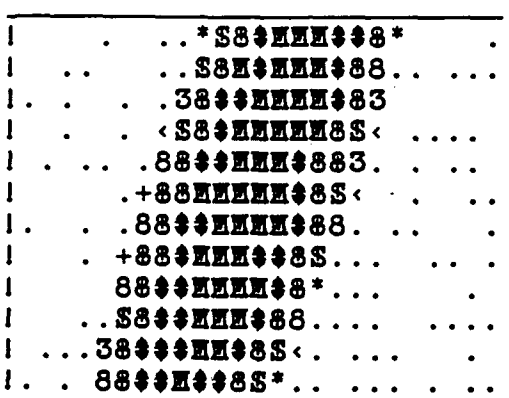


NOISE



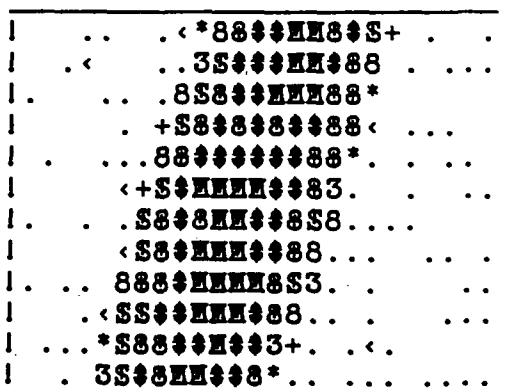
CLEAN

FSR= 0.4597



PROPAGATED

FSR_p= 0.0109

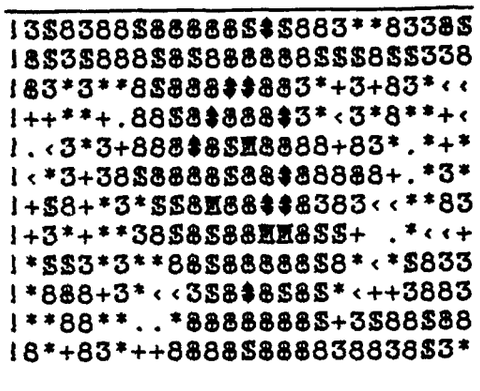


RECURSION

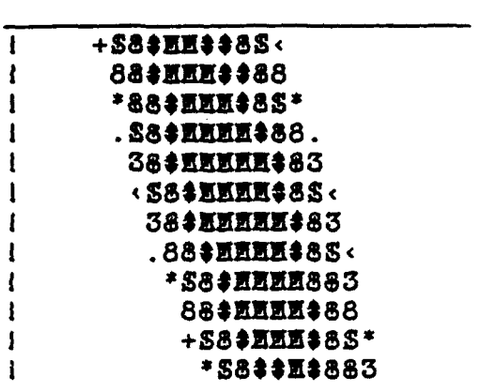
FSR_r= 0.0227

StdD= 0.3236

SET 15 - 300pixel
TRAINING

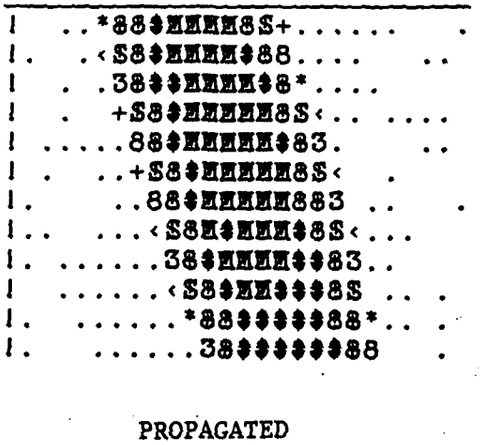


NOISE

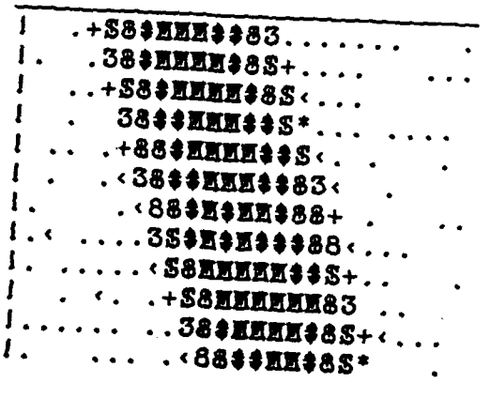


CLEAN

FSR= 0.5718



PROPAGATED



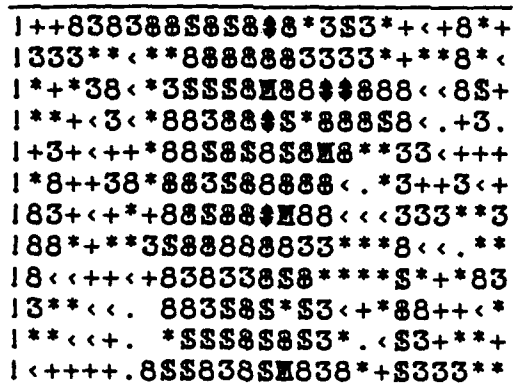
RECURSION

FSR_p= 0.0112

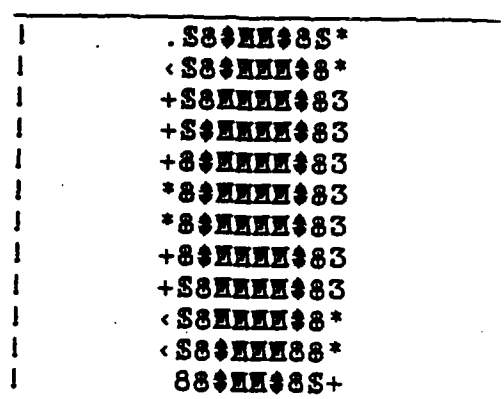
FSR_r= 0.0457

StdD= 0.3240

SET 16 - 300pixel
NON-TRAINING

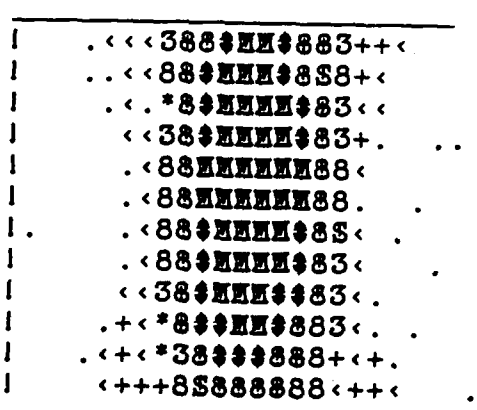


NOISE

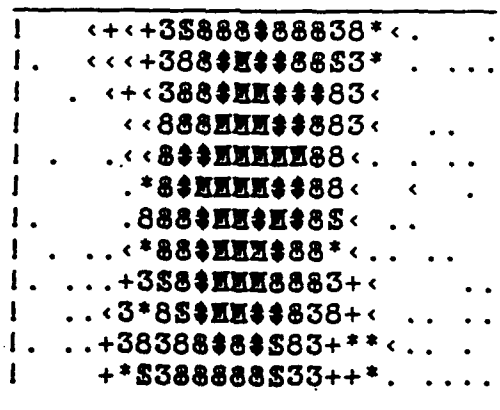


CLEAN

FSR= 0.6325



PROPAGATED



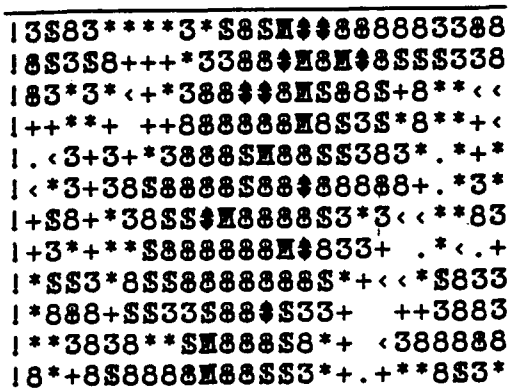
RECURSION

FSR_p= 0.0521

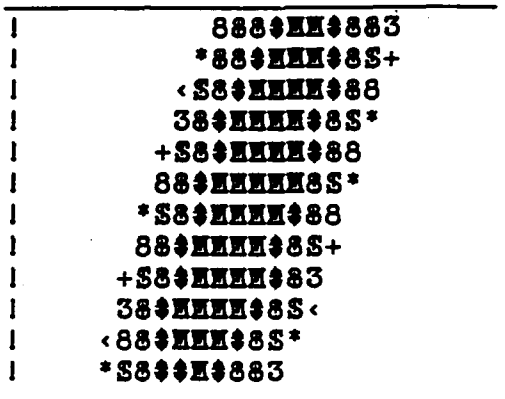
FSR_r= 0.1393

StdD= 0.3179

SET 17 - 300pixel
NON-TRAINING

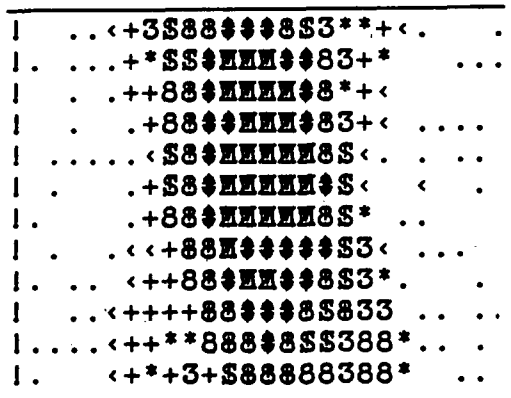


NOISE

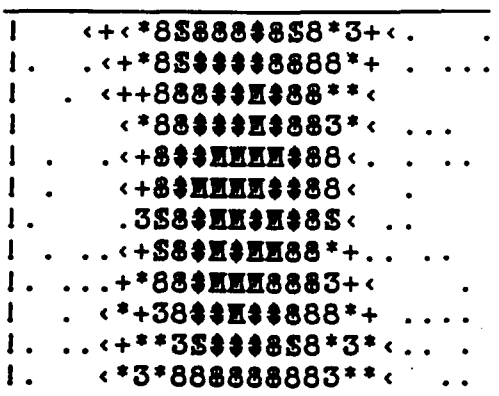


CLEAN

FSR= 0.4644



PROPAGATED

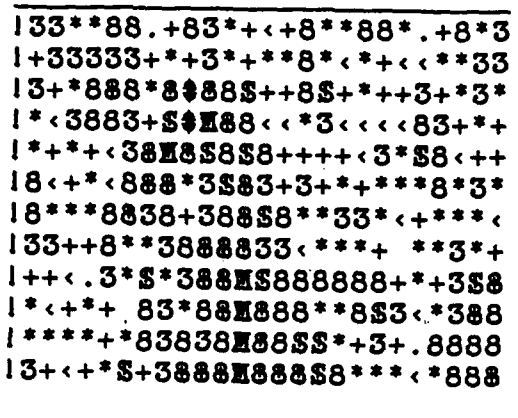


RECURSION

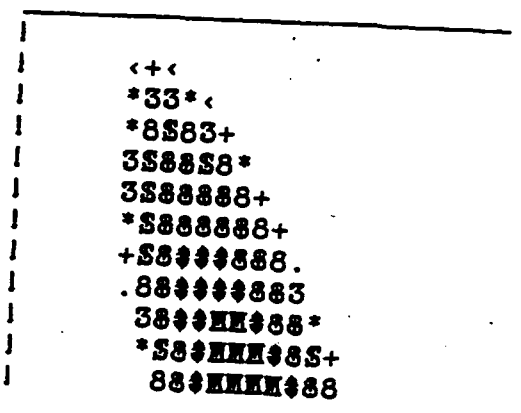
FSR_p= 0.3970

Fsr_r= 0.2807

StdD= 0.3242

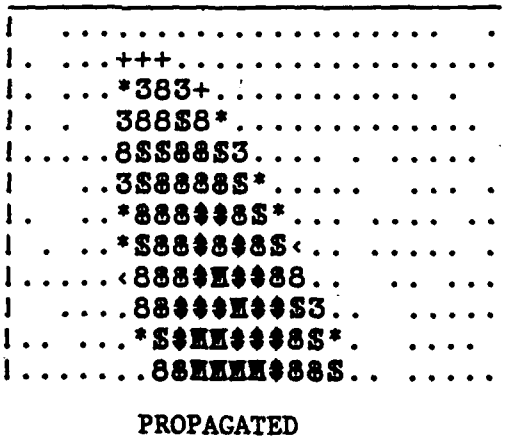


NOISE

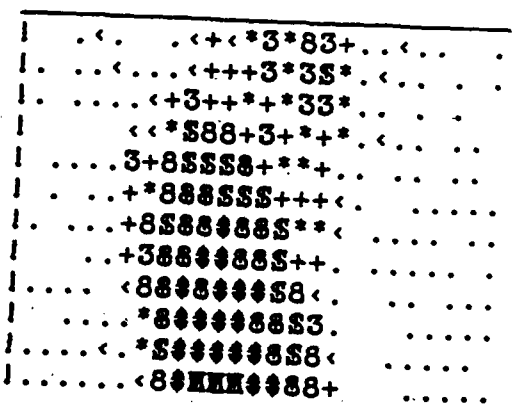


CLEAN

FSR= 0.8044



PROPAGATED



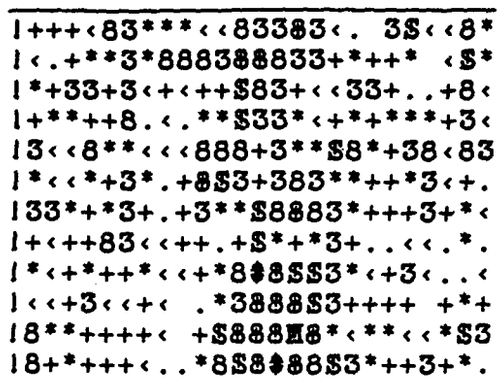
RECURSION

FSR_p= 0.0171

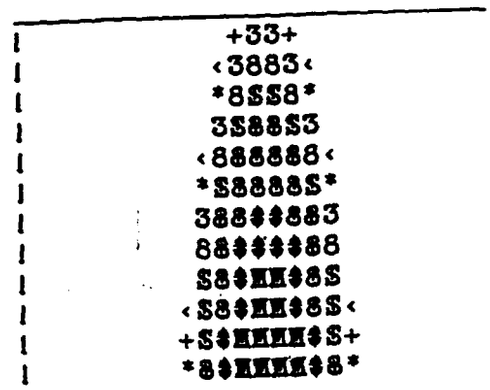
FSR_r= 0.2075

StdD= 0.2473

SET 19 - 300pixel
NON-TRAINING

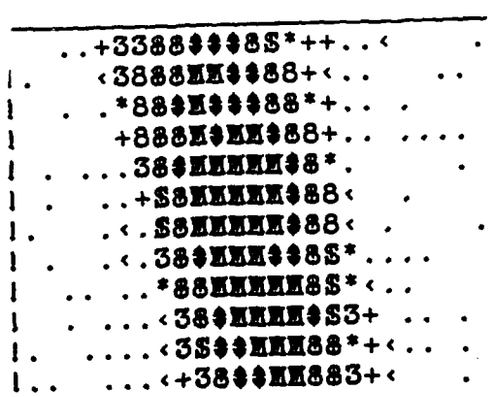


NOISE

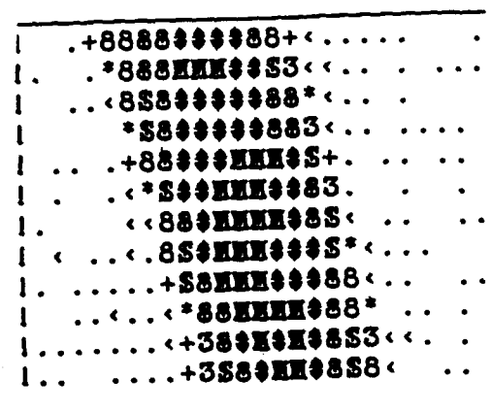


CLEAN

FSR= 0.8623



PROPAGATED



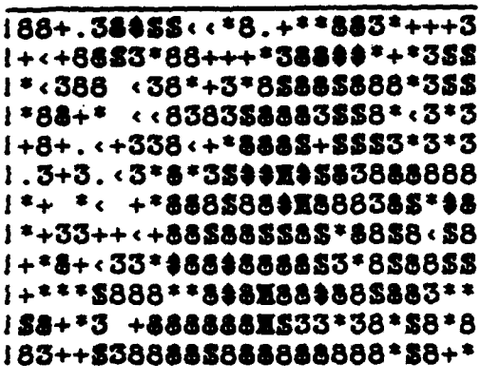
RECURSION

FSR_p= 0.3816

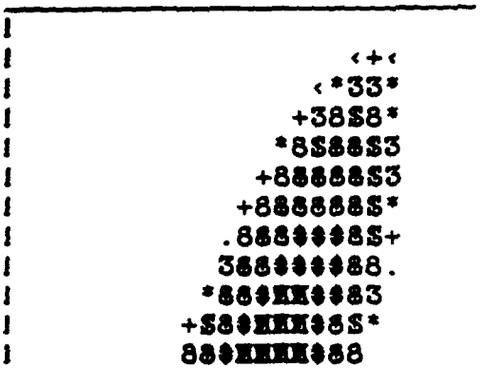
FSR_r= 0.4435

StdD= 0.2549

SET 20 - 300pixel
NON-TRAINING

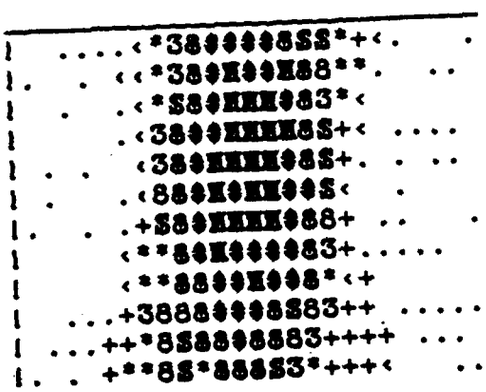


NOISE

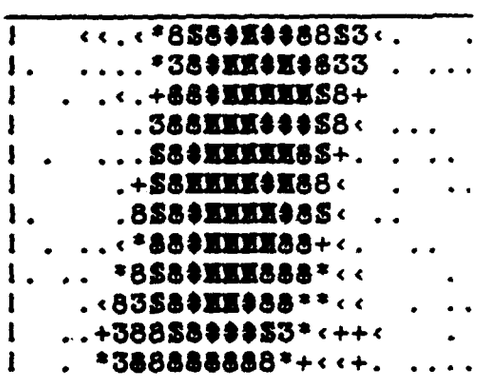


CLEAN

FSR= 1.1402



PROPAGATED



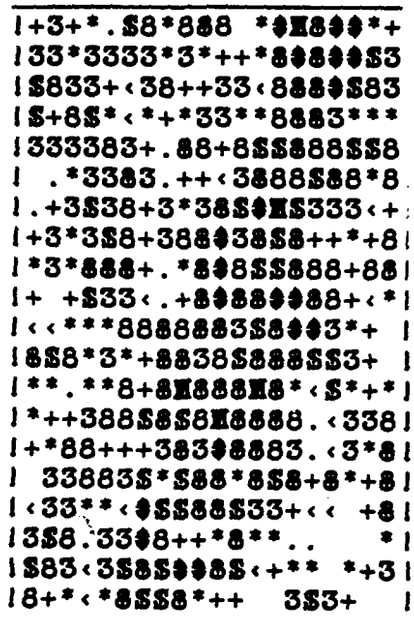
RECURSION

FSR_p= 1.5568

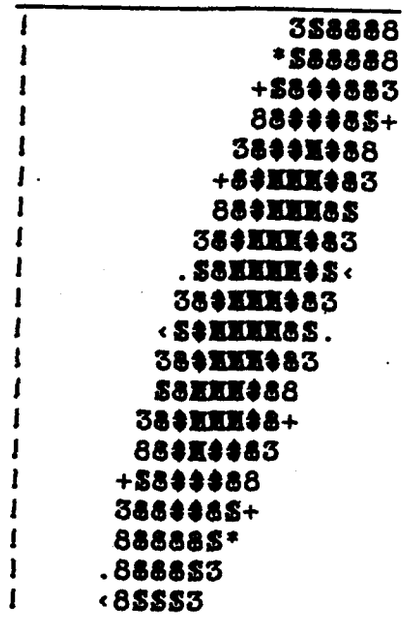
FSR_r= 1.6853

StdD= 0.2473

SET 1 - ABSOLUTE
400 - pixel



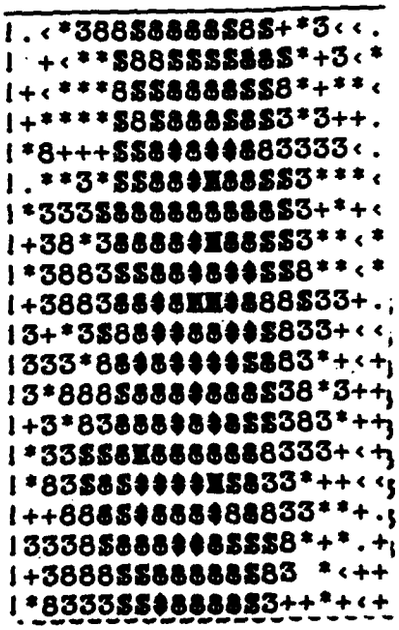
NOISE



NOISELESS

FSR= 0.8168

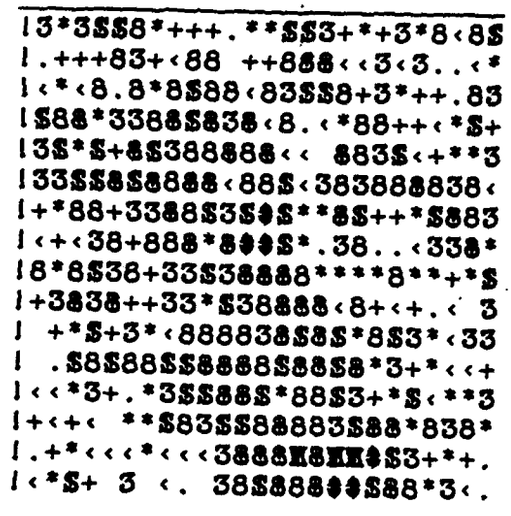
StdD= 0.0750



PROPAGATED

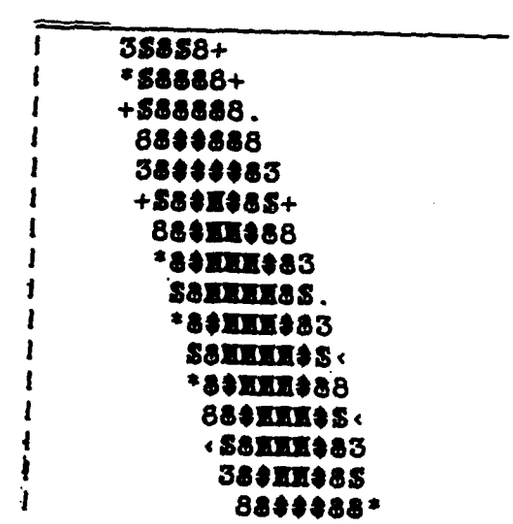
FSR= 1.2057

SET 1 - RELATIVE SCALE
400-Nodes- non-training

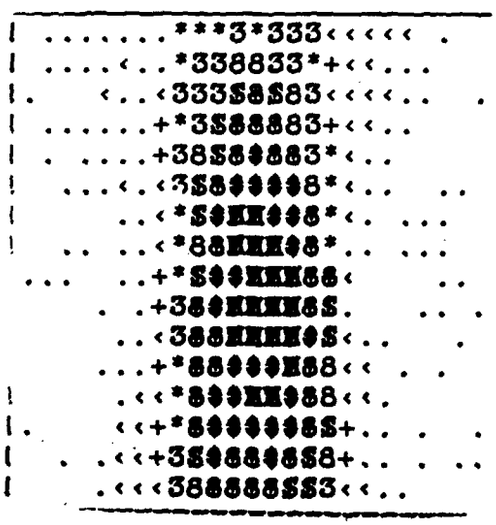


Noisy

FSR= 0.9151



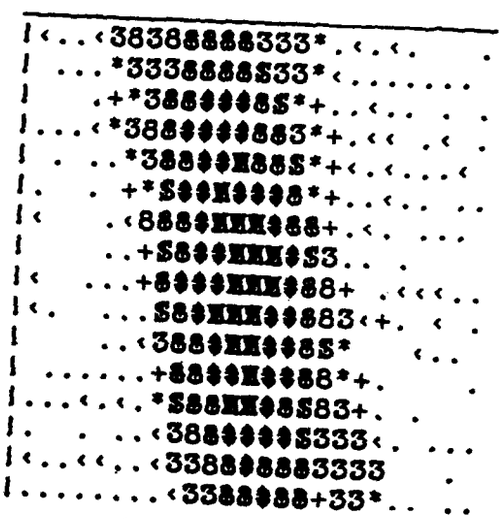
Noise-Free



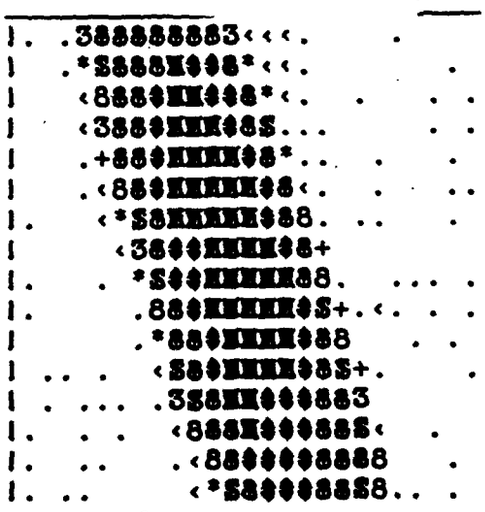
PROPAGATED

FSR= 0.6340

StdD= 0.2911

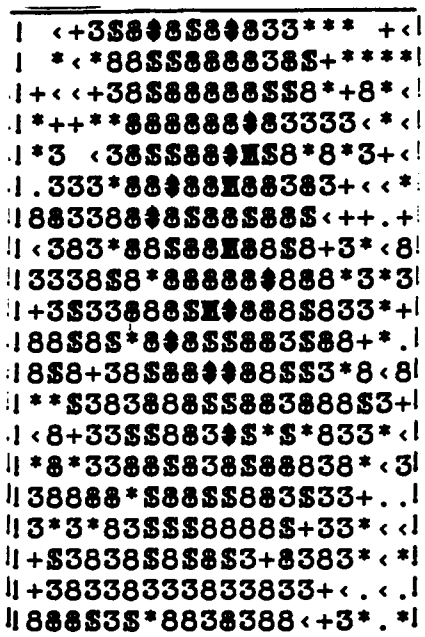


1st Recursion

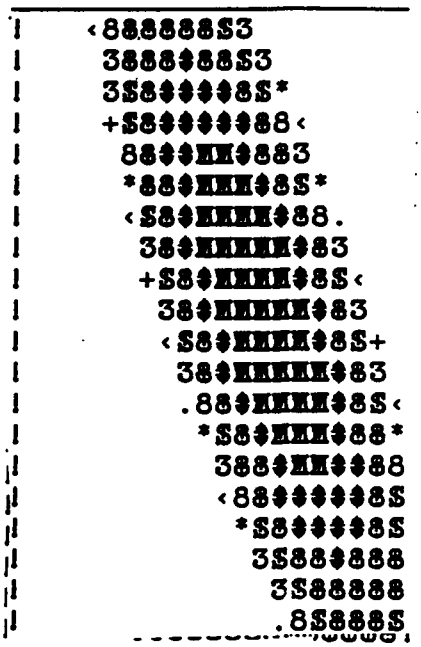


2nd Recursion

SET 2 - ABSOLUTE
400 pixel



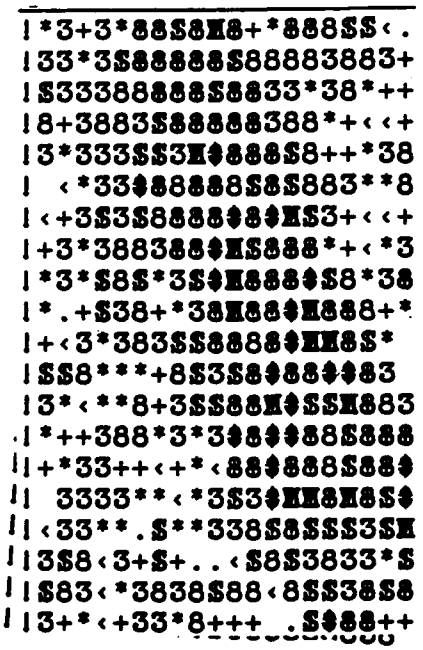
NOISE



NOISELESS

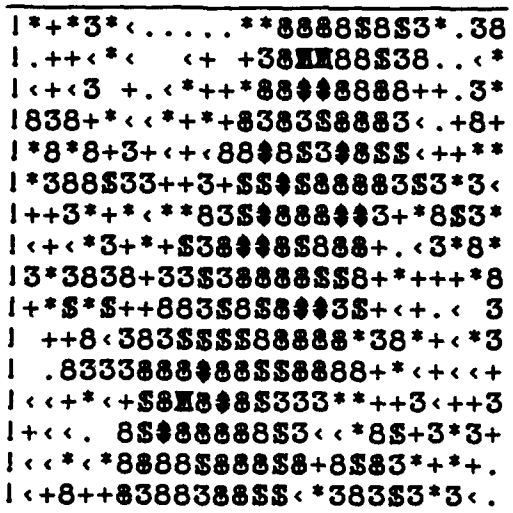
FSR= 0.5339 ;

StdD= 0.0453



PROPAGATED

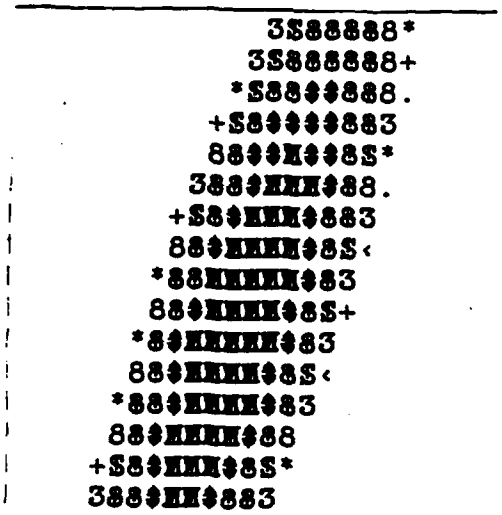
FSR= 1.2319



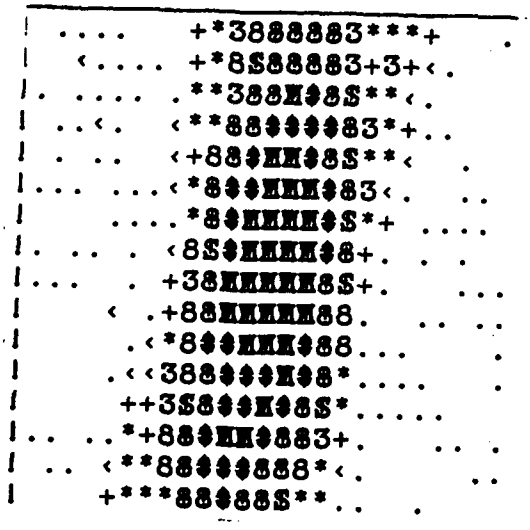
Noisy

FSR= 0.4856

StdD= 0.3059



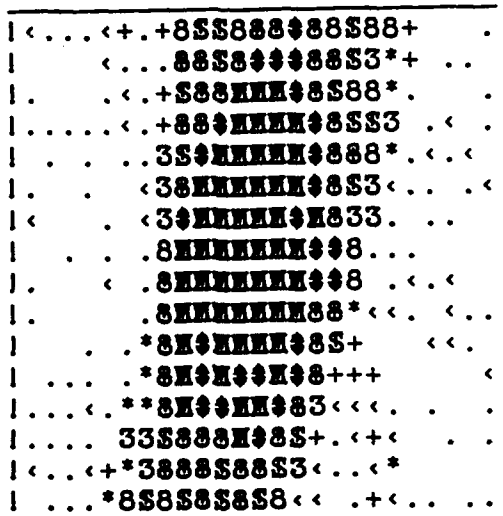
NOISELESS



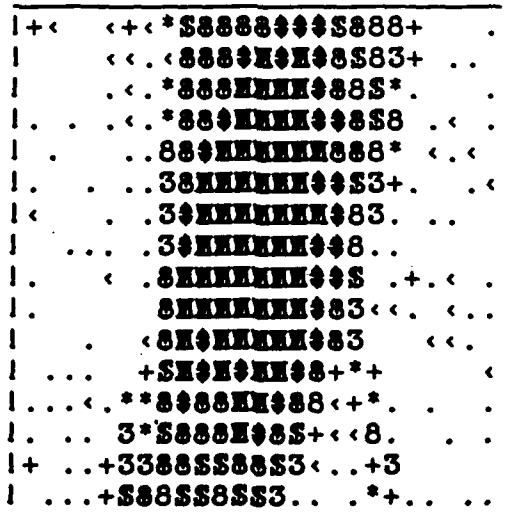
PROPAGATED

FSR= 0.3262

StdD= 0.3133

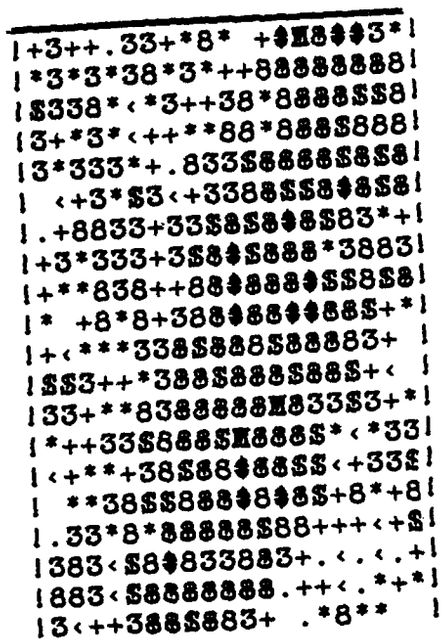


1st Recursion

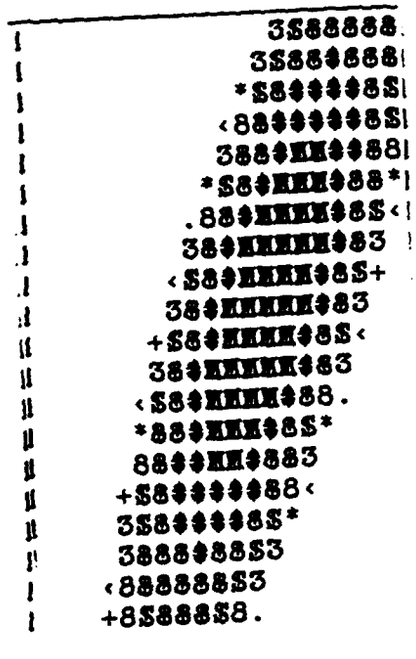


2nd Recursion

SET 3 - ABSOLUTE
400 - pixel



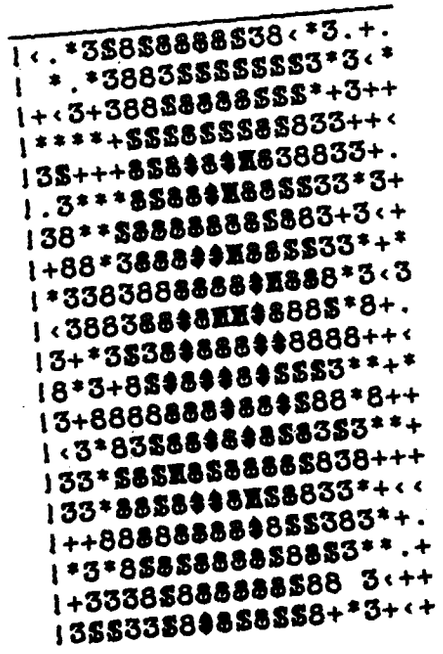
NOISY



NOISELESS

FSR= 0.4773

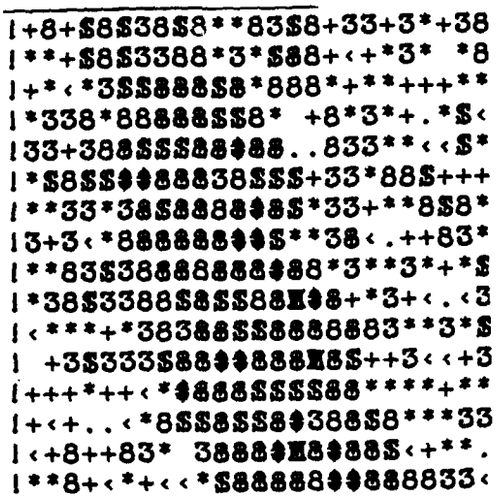
StdD = 0.0952



PROPAGATED

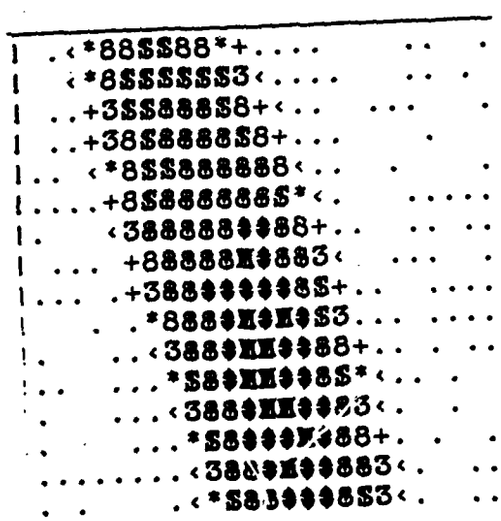
FSR= 1.1427

SET 3 - RELATIVE
400-Nodes, Training Set



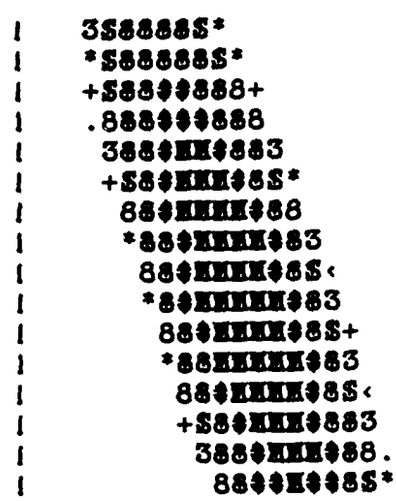
Noisy

FSR= 0.4693
StdD = 0.3059

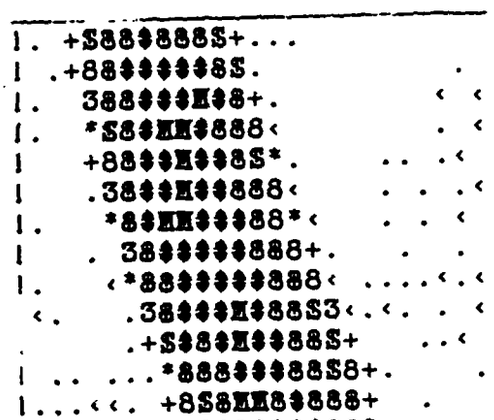


PROPAGATED

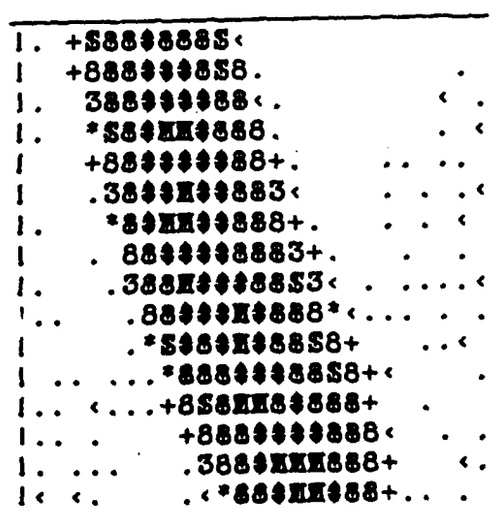
FSR= 0.2225
StdD = 0.3133



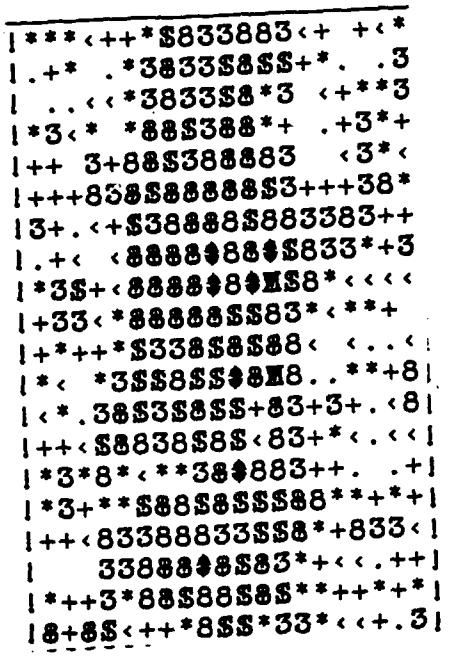
Noise-Free



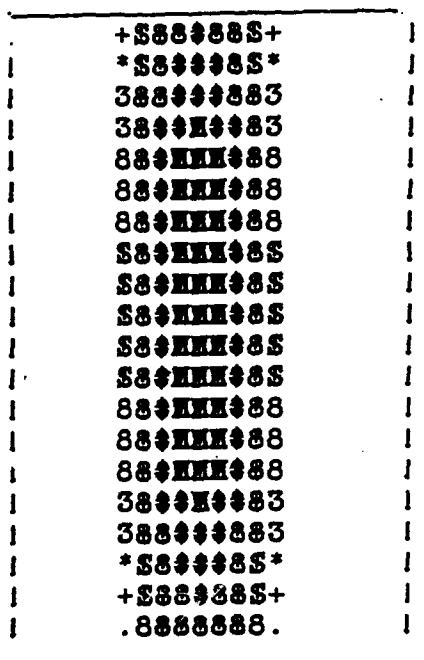
1st Recursion



2nd Recursion



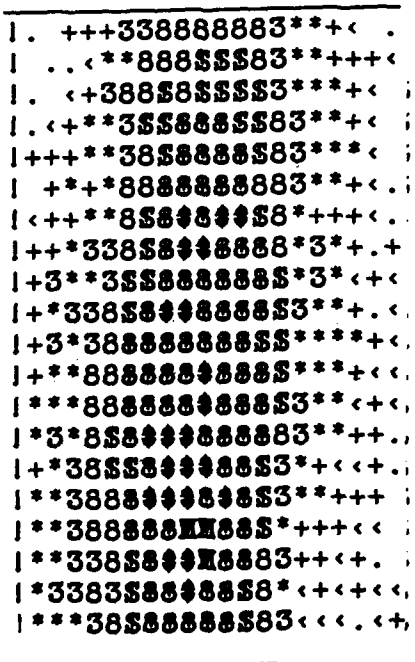
NOISE



NOISELESS

FSR= 0.5392

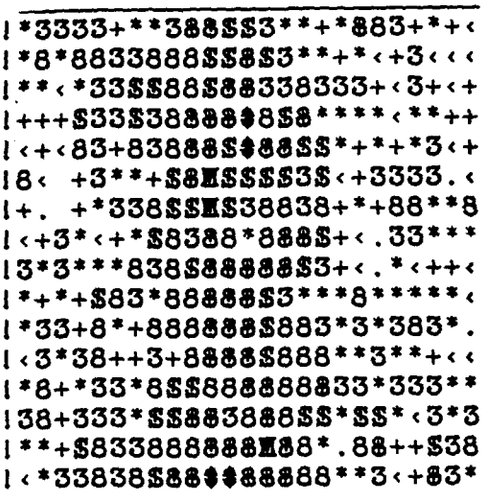
StdD = 0.0800



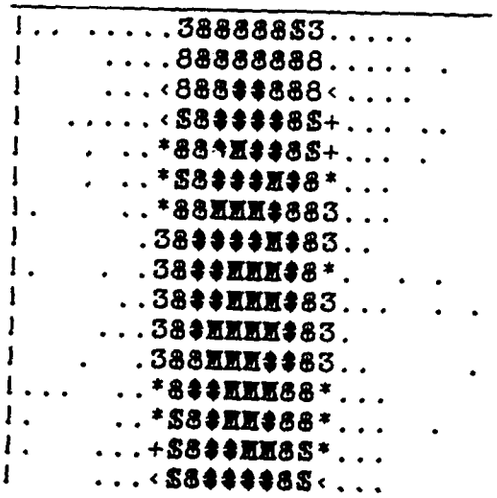
PROPAGATED

FSR= 0.2586

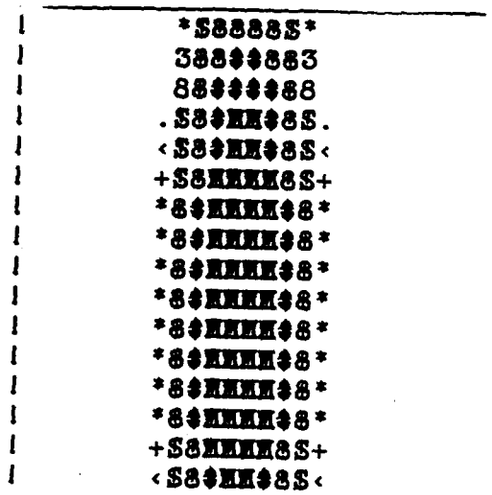
SET 5 - RELATIVE
400 - NODES, TRAINING SET



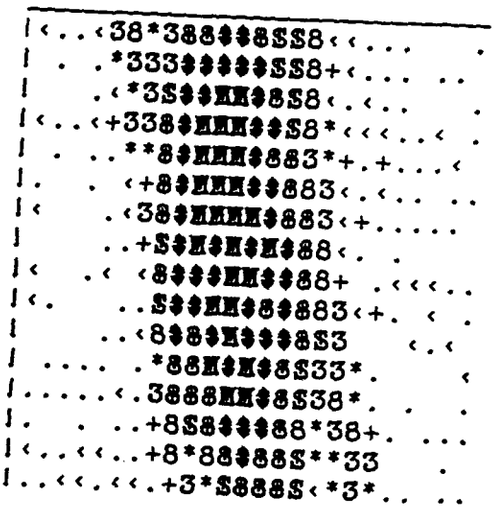
NOISE
FSR = 0.7000
StdD = 0.3093



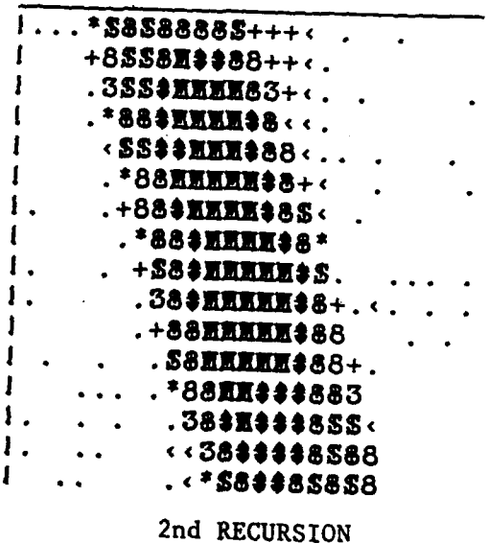
PROPAGATED
FSR = 0.1699
StdD = 0.3098



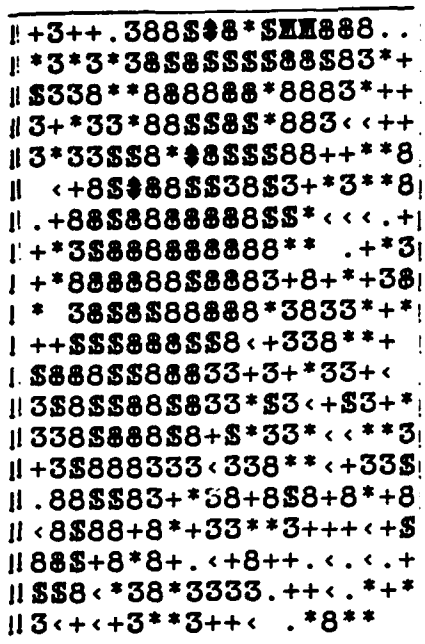
NOISELESS



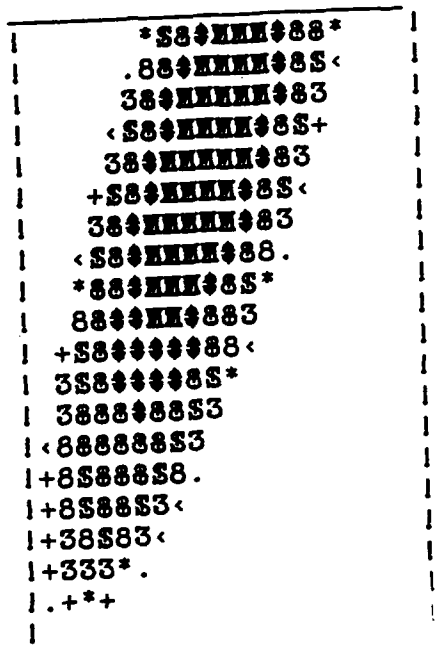
1st RECURSION



2nd RECURSION



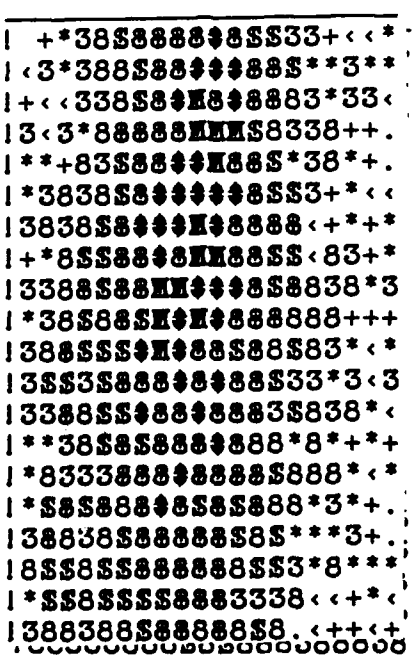
NOISE



NOISELESS

FSR = 0.5756

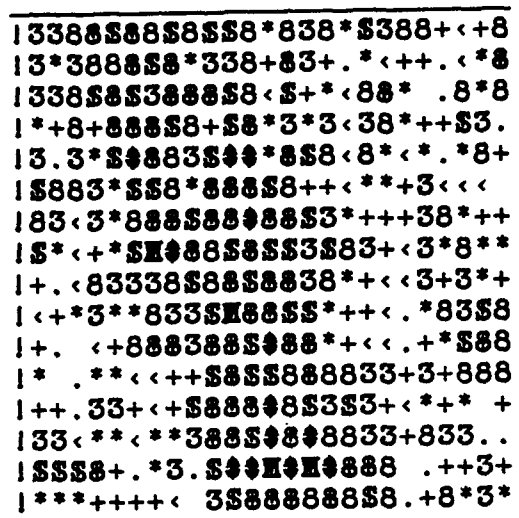
StdD = 0.0763



PROPAGATED

FSR = 0.7304

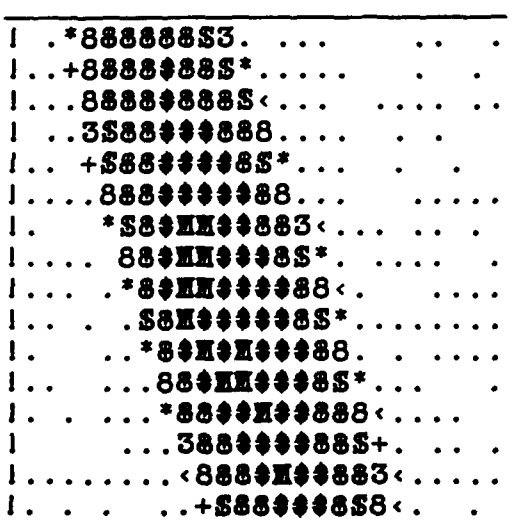
SET 6 - RELATIVE
400-Nodes, Training Set



NOISY

FSR = 0.6237

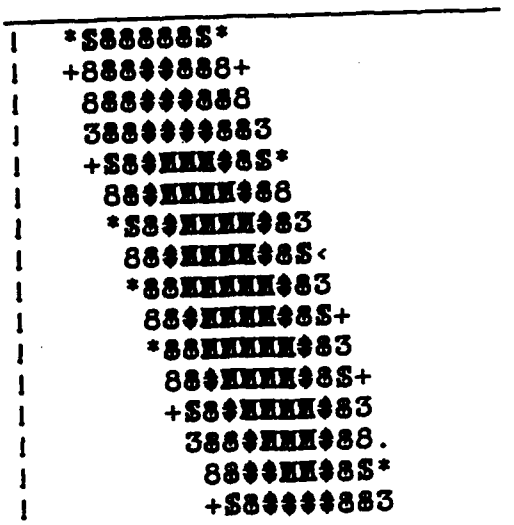
StdD = 0.3057



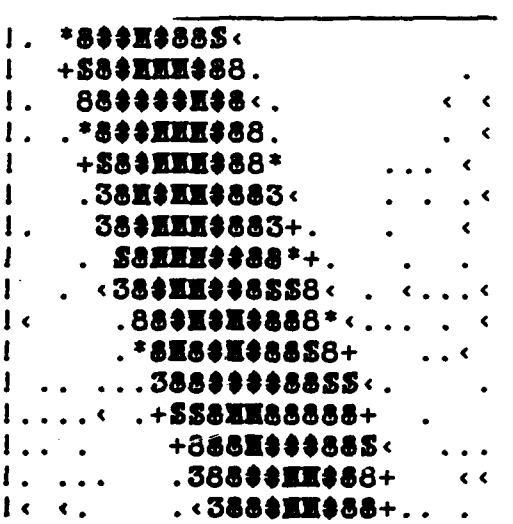
PROPAGATED

FSR = 0.1614

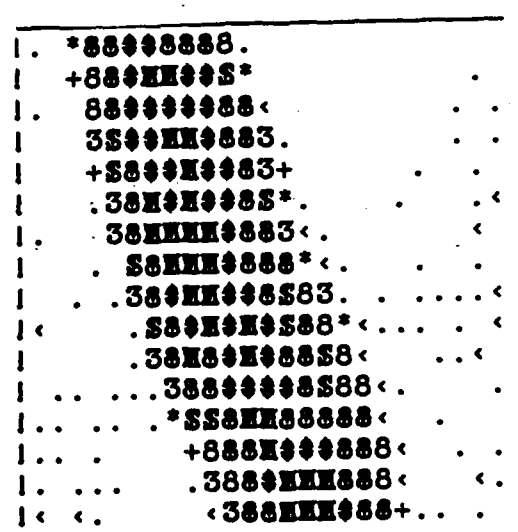
StdD = 0.3152



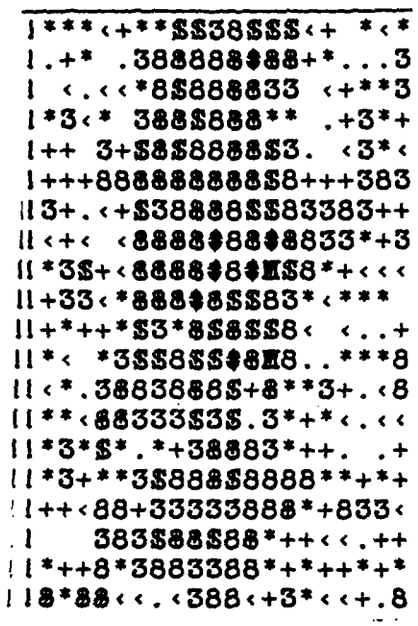
NOISELESS



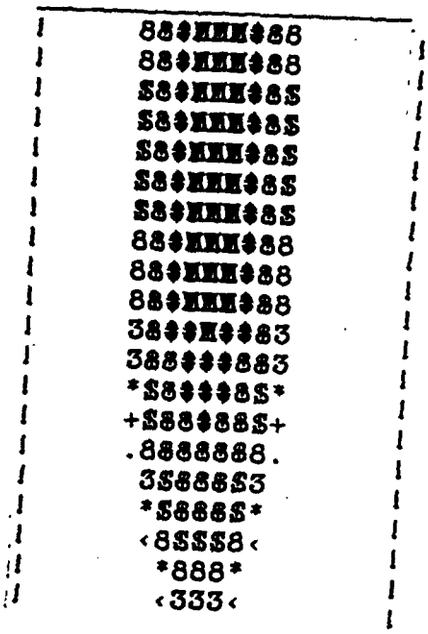
1st RECURSION



2nd RECURSION

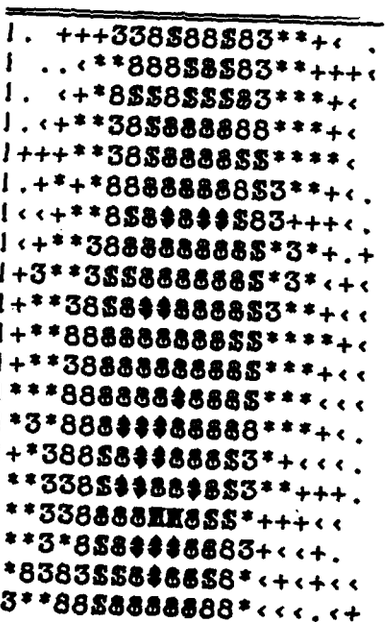


NOISY



NOISELESS

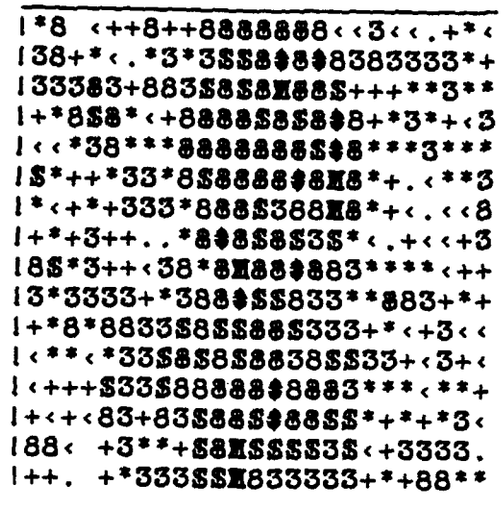
FSR = 0.5805
StdD = 0.0766



PROPAGATED

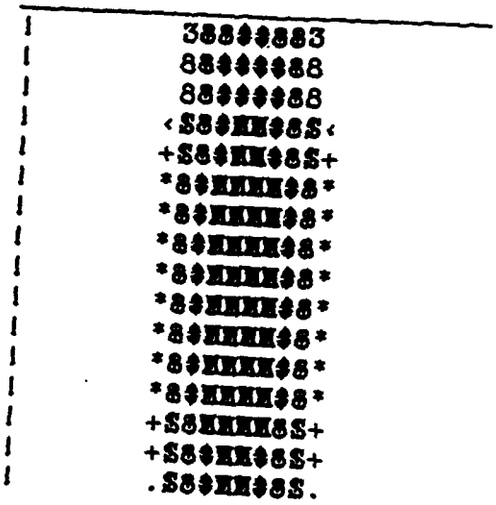
FSR = 0.4234

SET 7 - RELATIVE
400-Node, Training Set

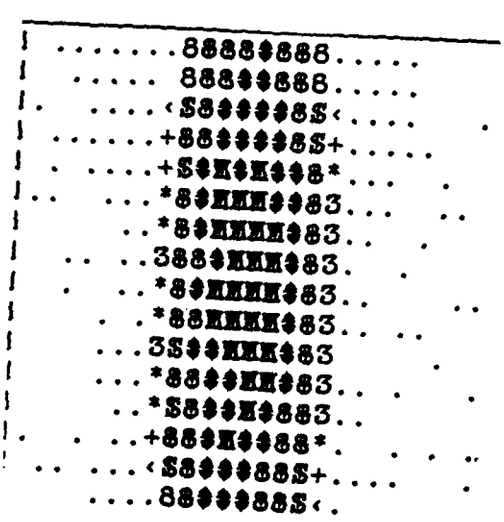


NOISY

FSR = 0.5422
StdD = 0.3040



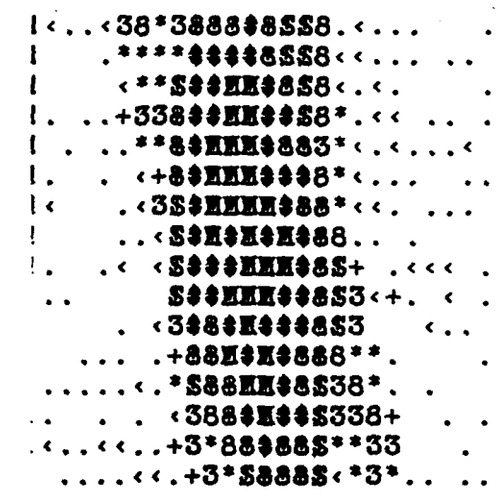
NOISE-FREE



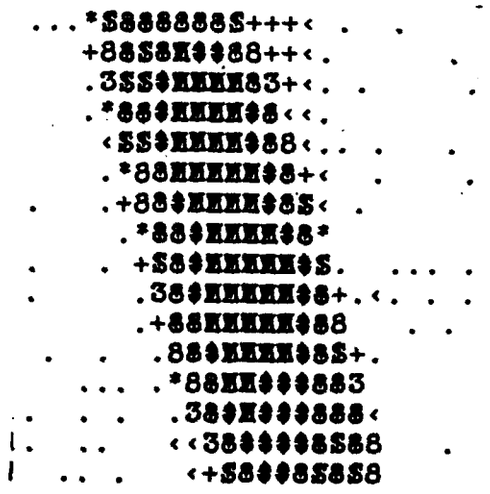
PROPAGATED

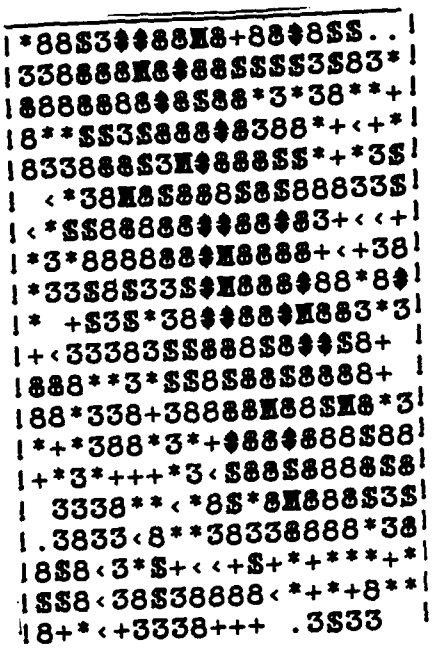
FSR = 0.2075

StdD = 0.4075

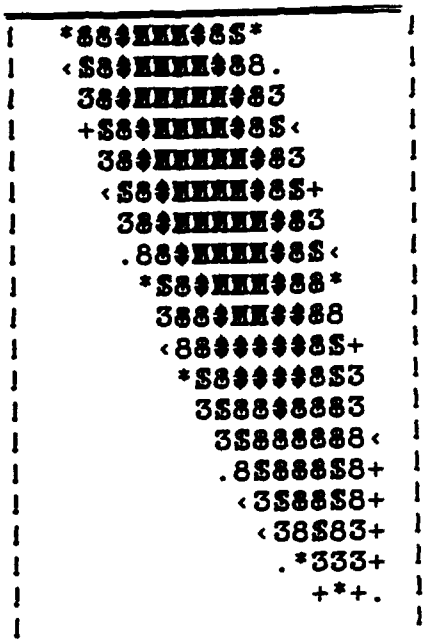


1st RECURSION





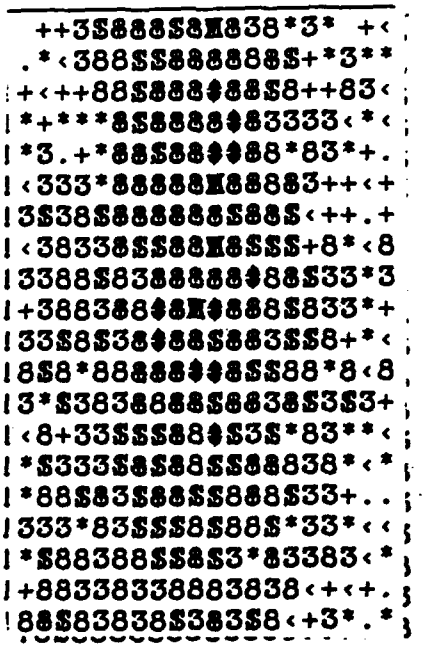
NOISE



NOISELESS

FSR = 0.6351

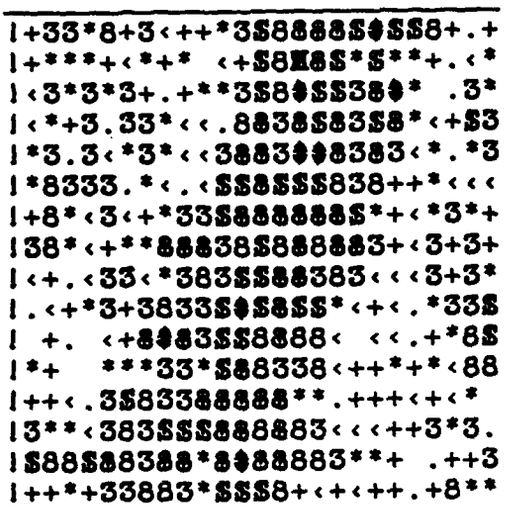
StdD = 0.0763



PROPAGATED

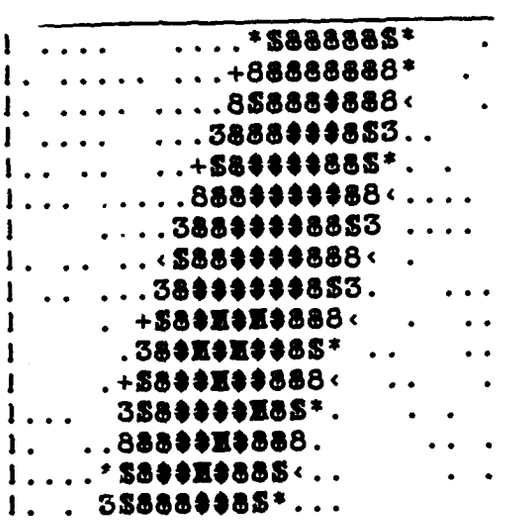
FSR = 0.8975

SET 8 - RELATIVE
400-Node, Training Set



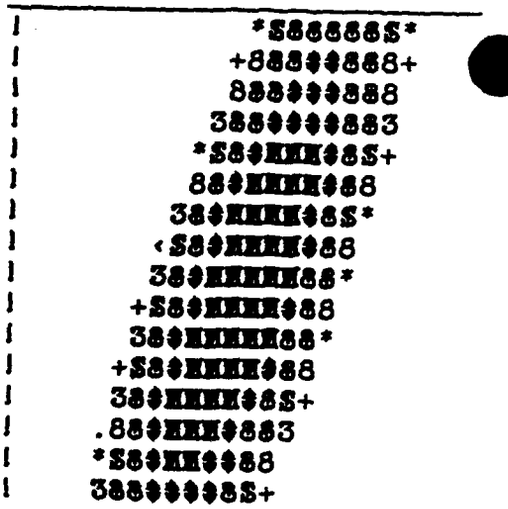
NOISE

FSR = 0.5860
StdD = 0.3057

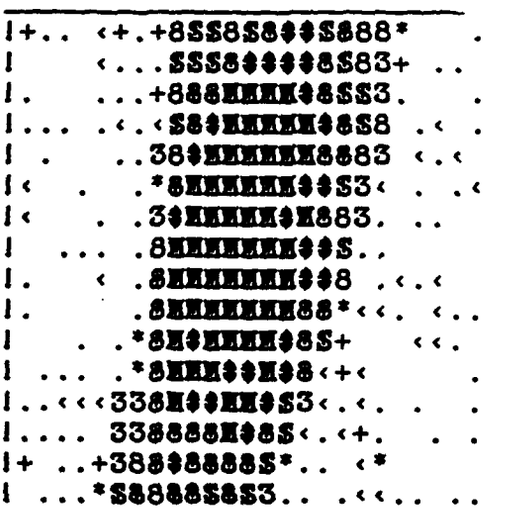


CLEAN

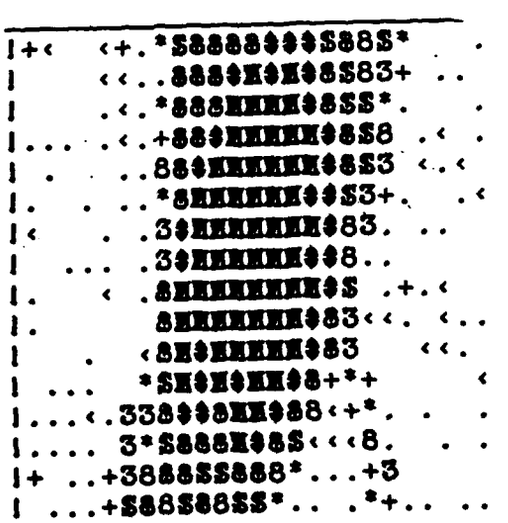
FSR = 0.1598
StdD = 0.3152



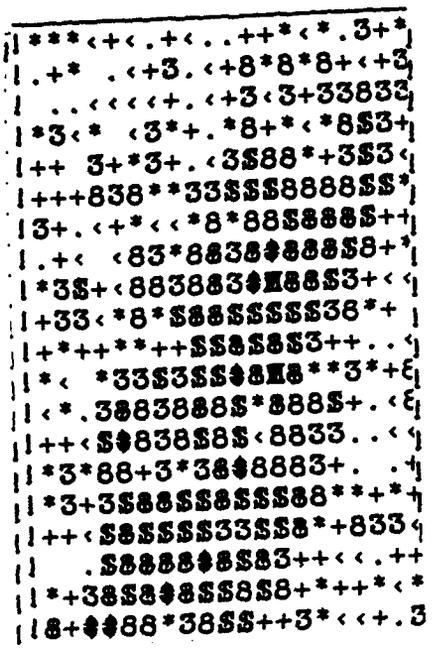
NOISELESS



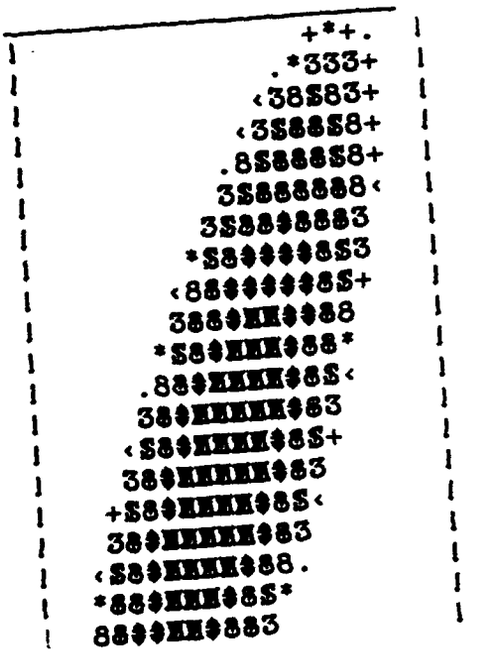
1st PROPAGATION



2nd PROPAGATION

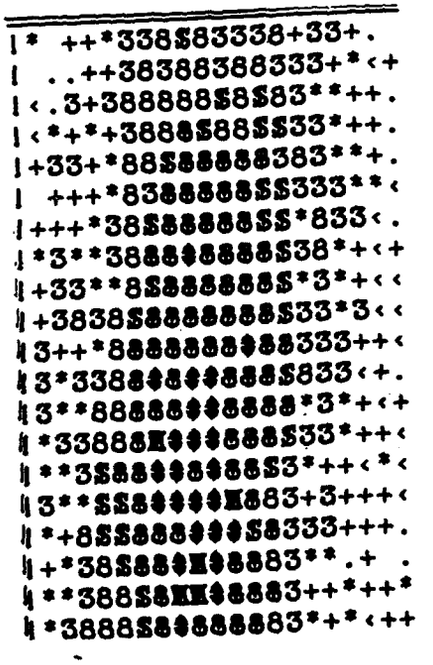


NOISE



NOISELESS

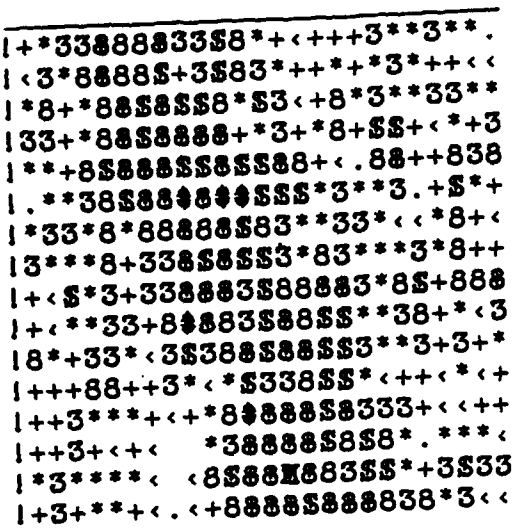
FSR = 0.5684
StdD = 0.0771



PROPAGATED

FSR = 0.6248

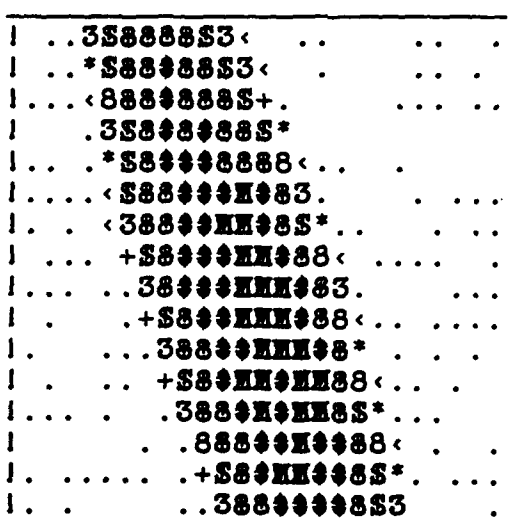
SET 9 - RELATIVE
400-Node, Training Set



NOISY

FSR = 0.6028

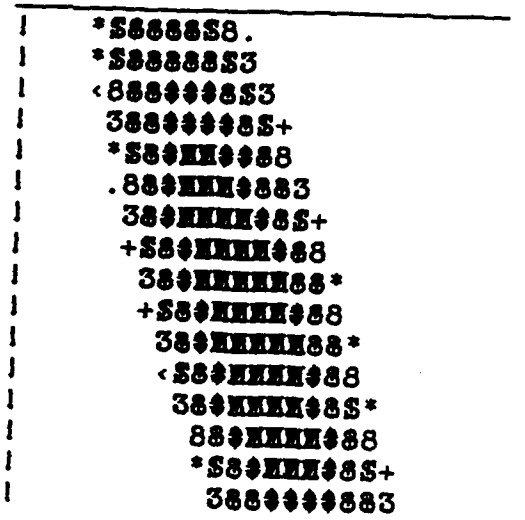
StdD = 0.3060



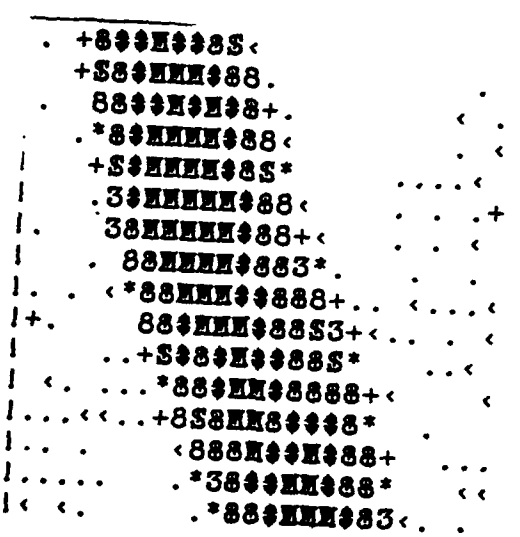
PROPAGATED

FSR = 0.1531

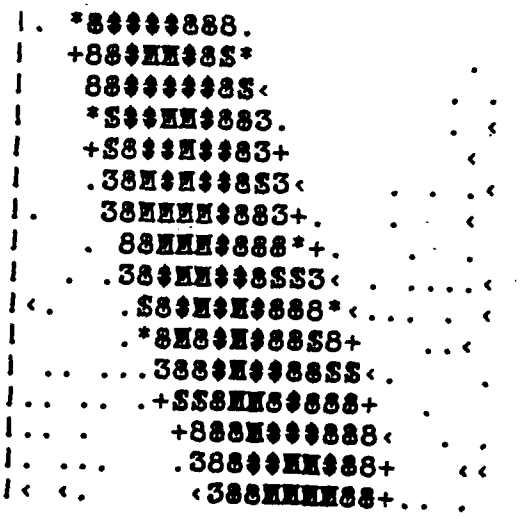
StdD = 0.3141



NOISELESS



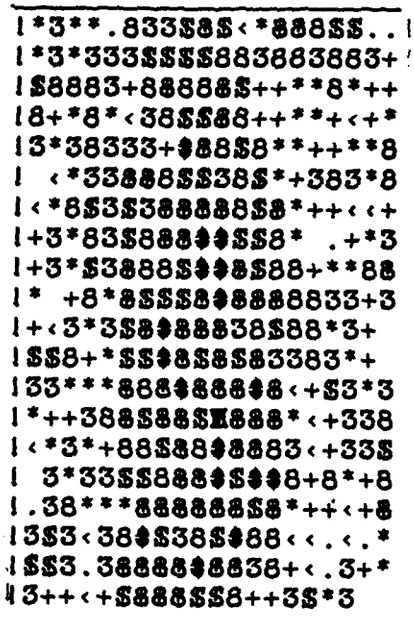
1st PROPAGATION



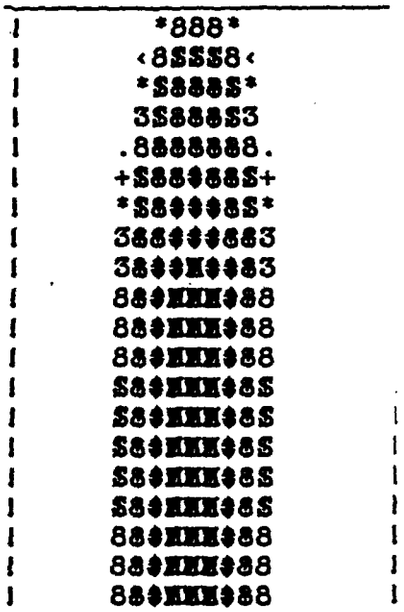
2nd PROPAGATION

H

SET 10 - ABSOLUTE
400-pixel

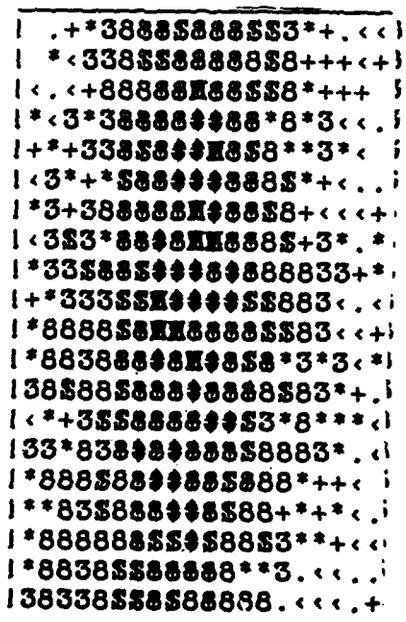


NOISY



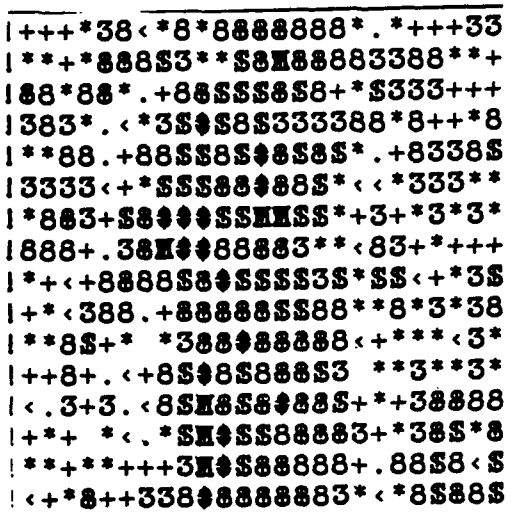
NOISELESS

FSR = 0.5935
StdD = 0.0778



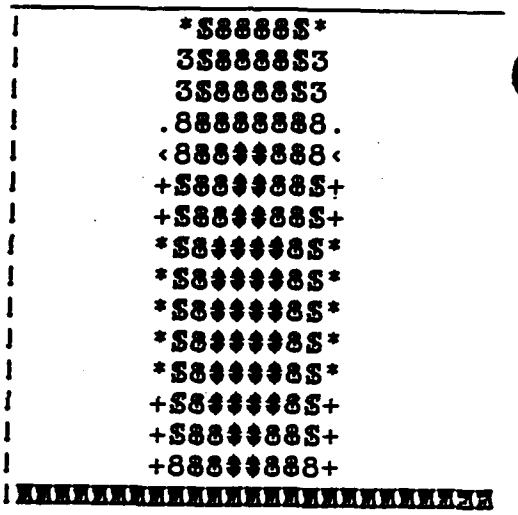
PROPAGATED

FSR = 0.4070

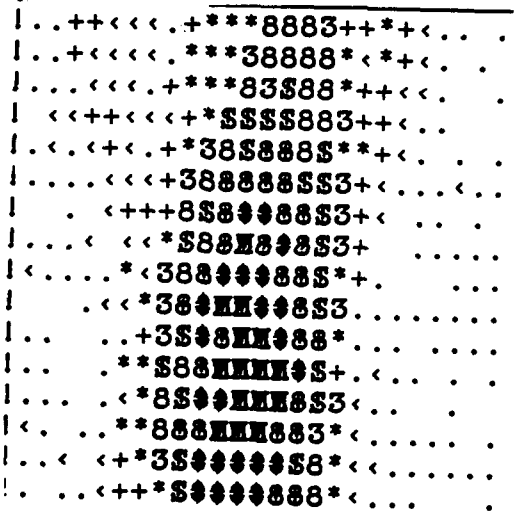


NOISY

FSR = 0.8010
StdD = 0.3333

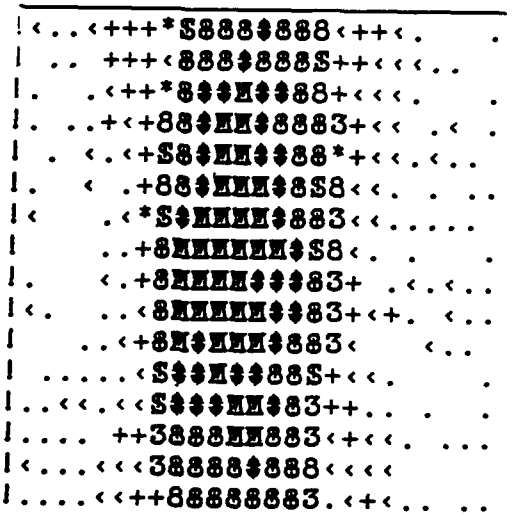


NOISELESS

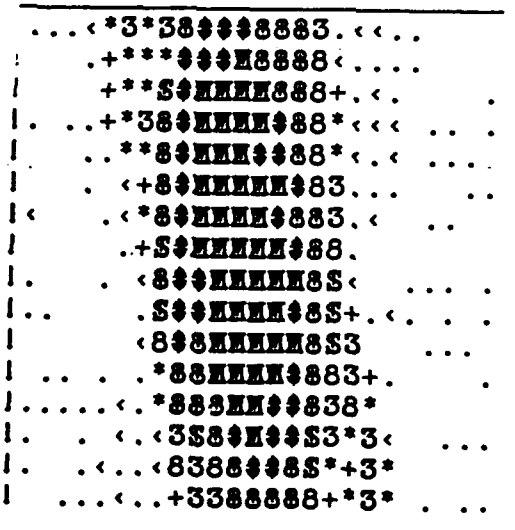


PROPAGATED

FSR = 0.3096
StdD = 0.3103

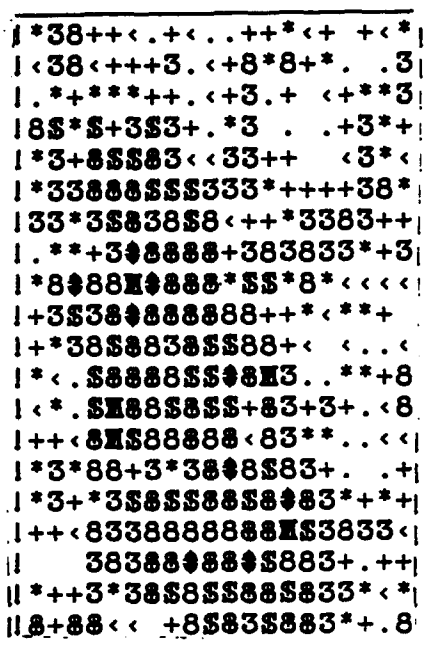


1st RECURSION

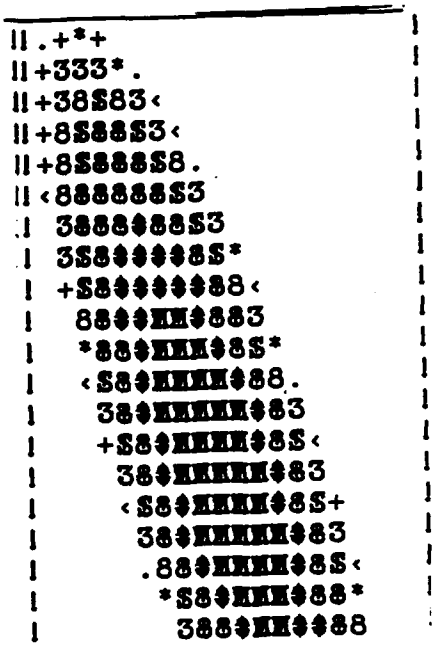


2nd RECURSION

SET 11 - ABSOLUTE
400-pixel

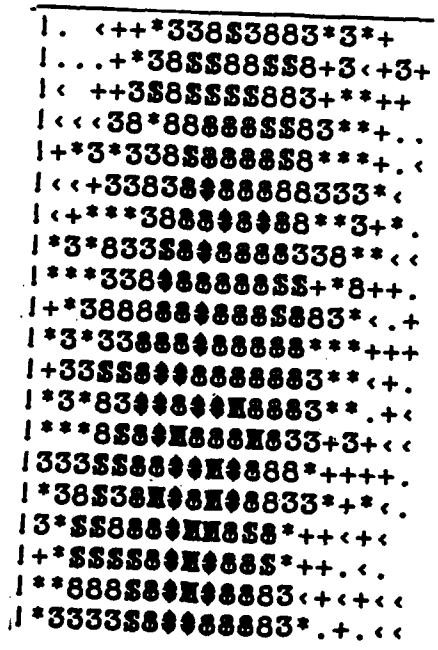


NOISY



NOISELESS

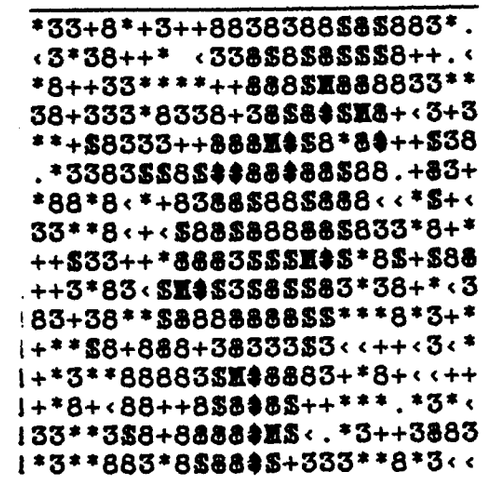
FSR = 0.5690
StdD = 0.0771



PROPAGATED

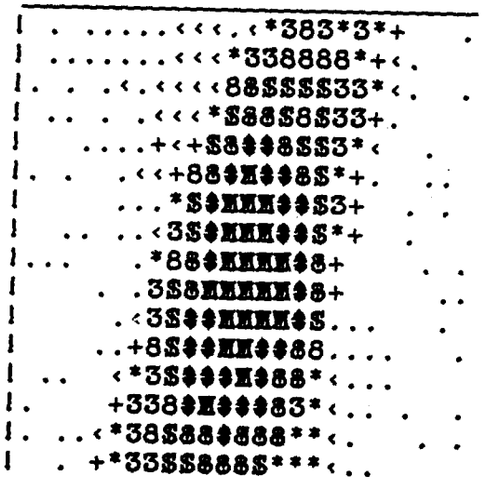
FSR = 0.9492

SET 11 - RELATIVE
400-Node, NON-TRAINING



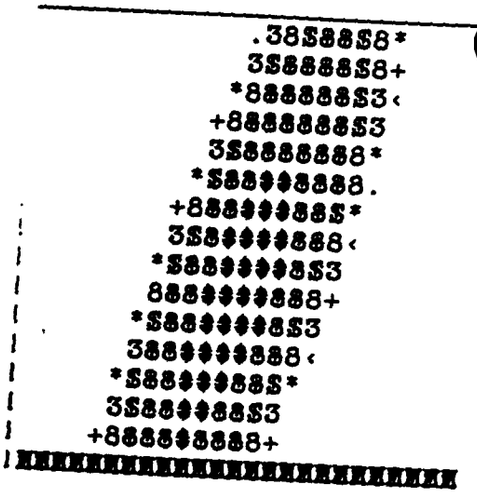
NOISY

FSR = 0.7834
StdD = 0.3333

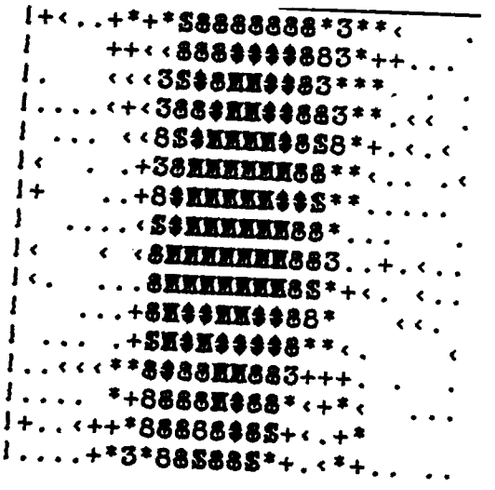


PROPAGATED

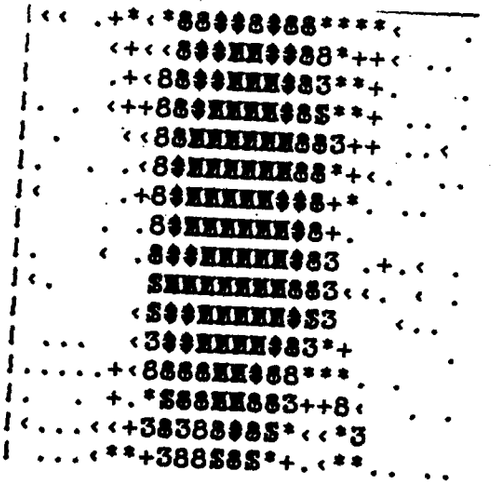
FSR = 0.2488
StdD = 0.3141



NOISELESS

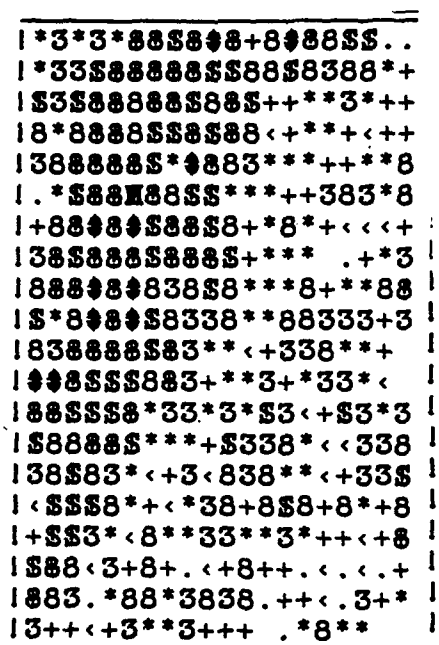


1st RECURSION

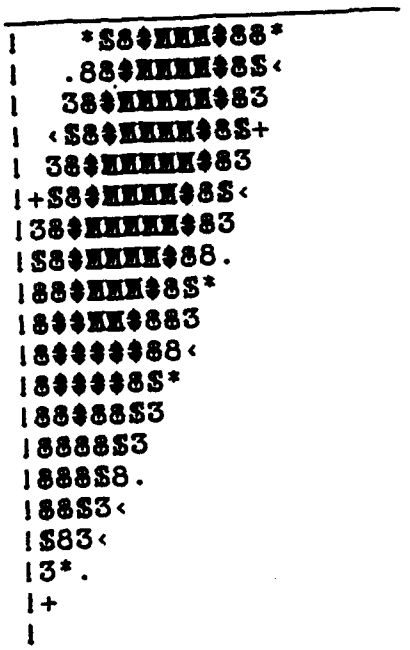


2nd RECURSION

SET 12 - ABSOLUTE
400-pixel



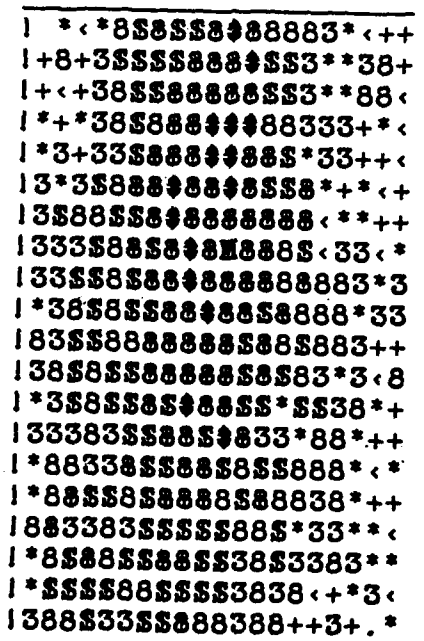
NOISE



NOISELESS

FSR = 0.5808

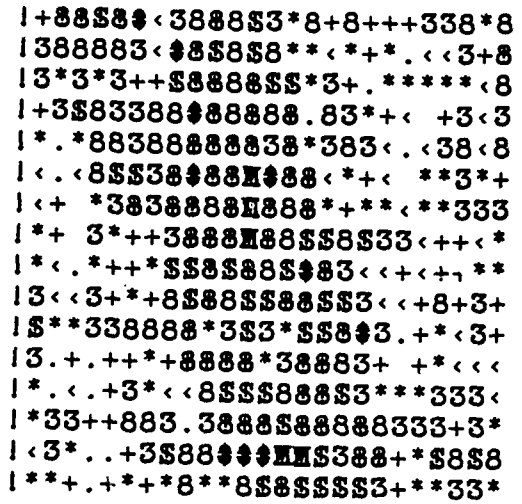
StdD = 0.0772



PROPAGATED

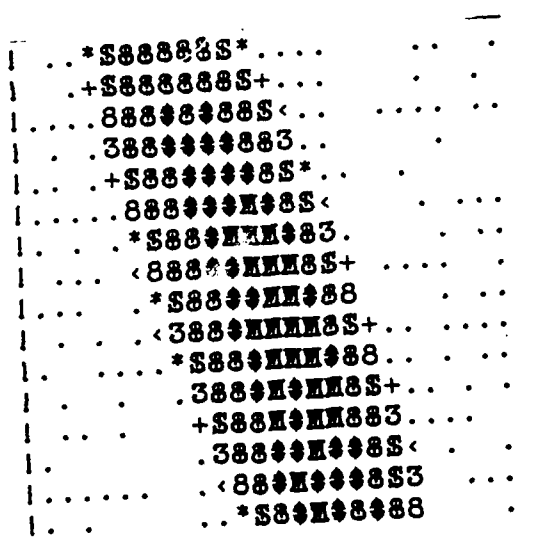
FSR = 1.3403

SET 12 - RELATIVE
400, Training Set



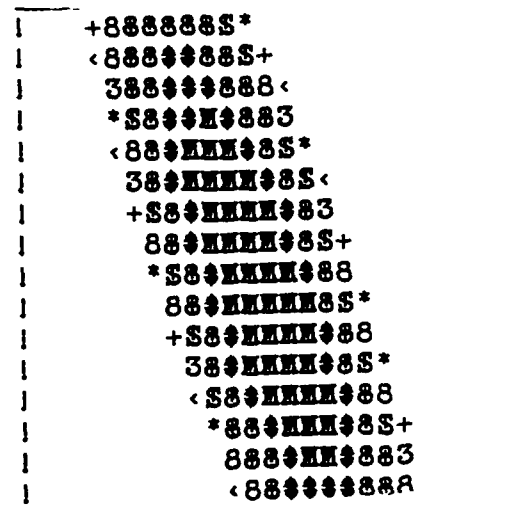
NOISY

FSR = 0.6433
StdD = 0.3054

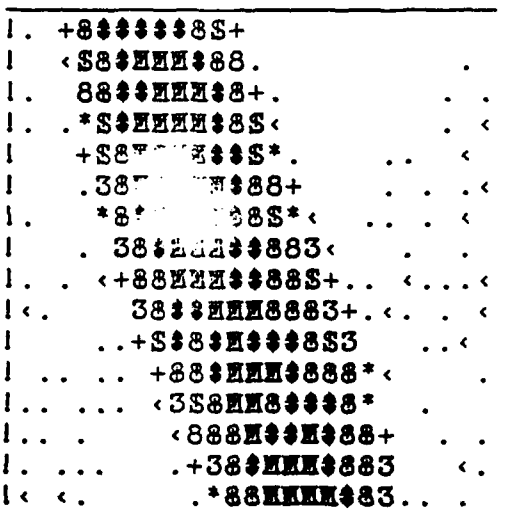


PROPAGATED

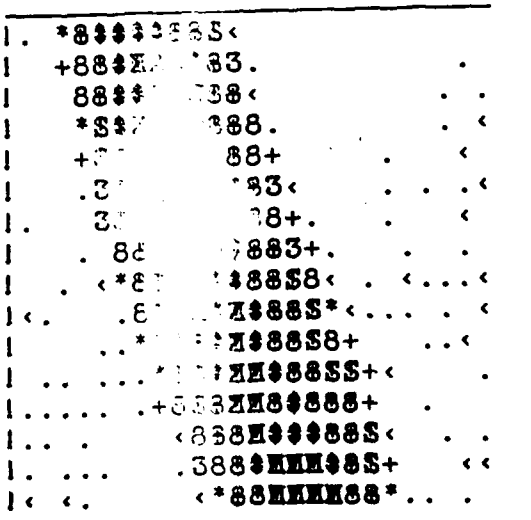
FSR = 0.1507
StdD = 0.3147



NOISELESS



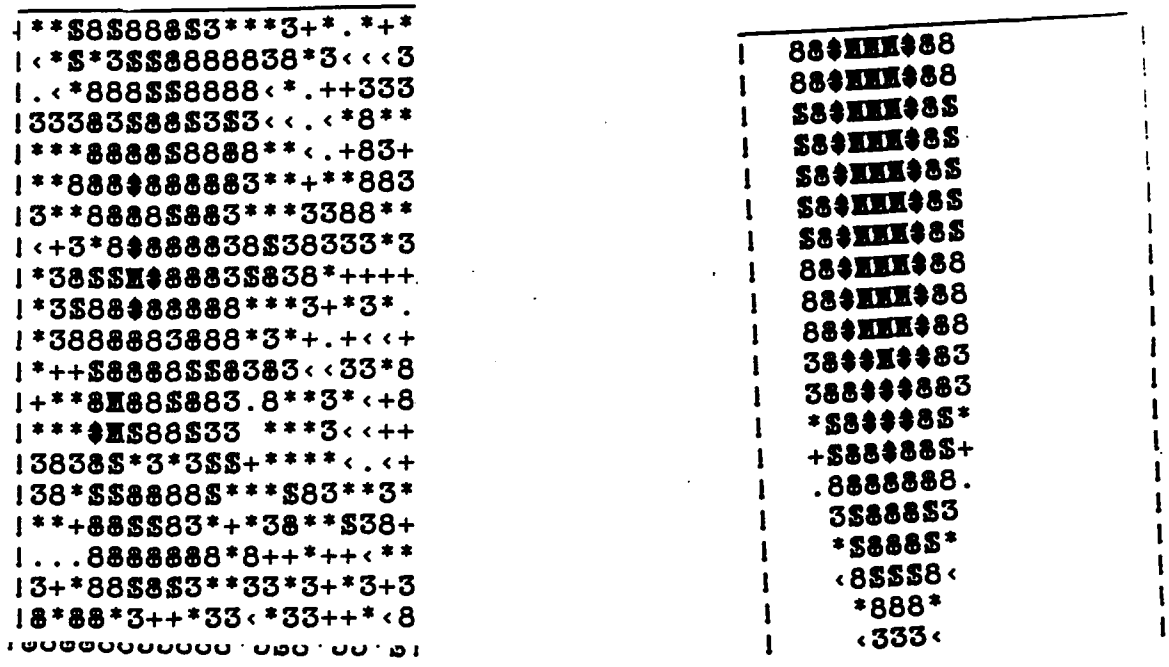
1st RECURSION



2nd RECURSION

H

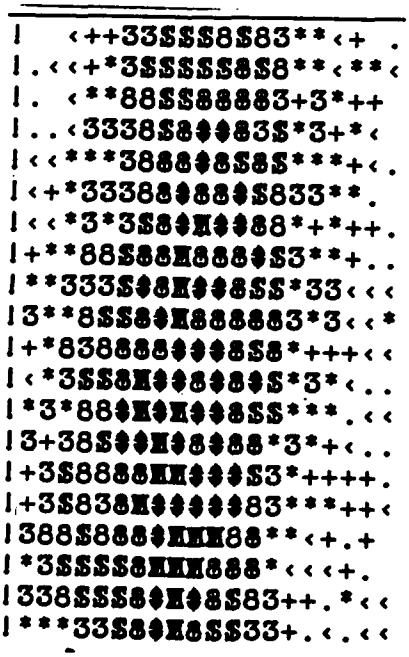
SET 13 - ABSOLUTE
400-pixel



NOISE

NOISELESS

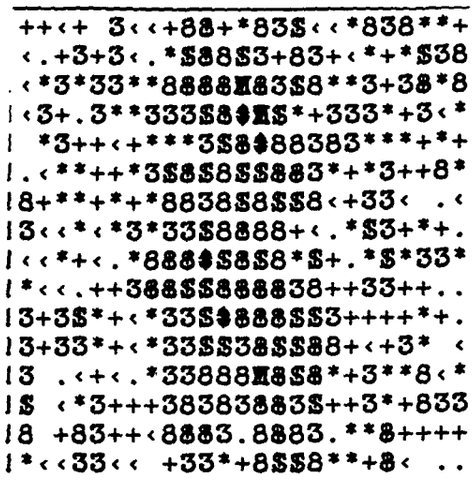
FSR = 0.6060
StdD = 0.0766



PROPAGATED

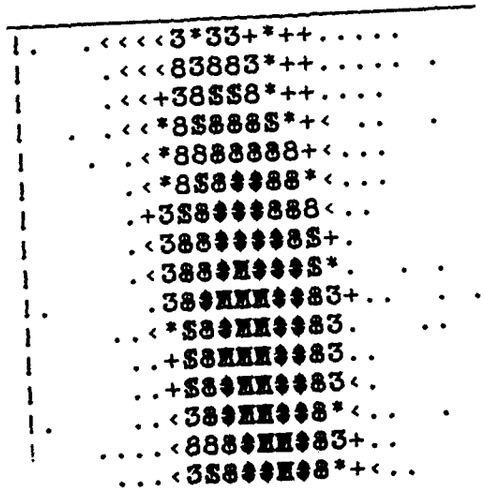
FSR = 0.9937

SET 13 - RELATIVE
400-Node, NON-TRAINING



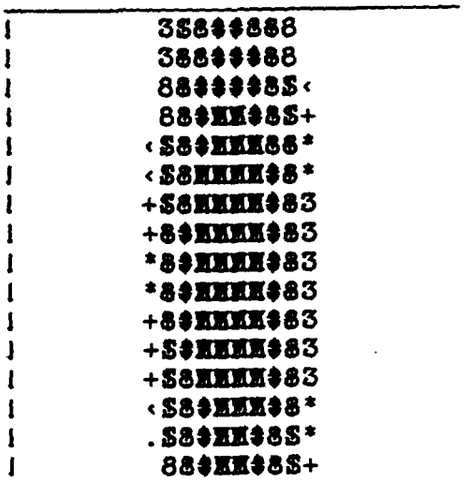
NOISY

FSR = 0.7536
StdD = 0.3109

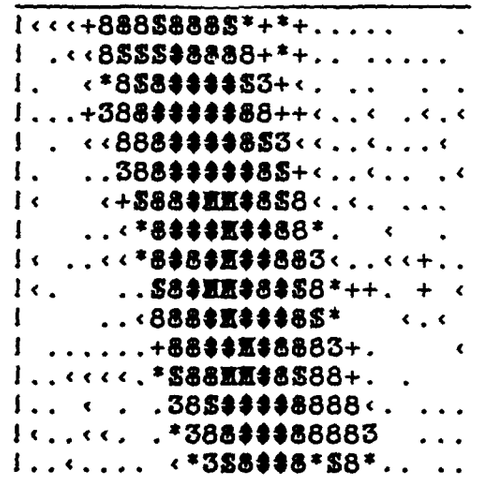


PROPAGATED

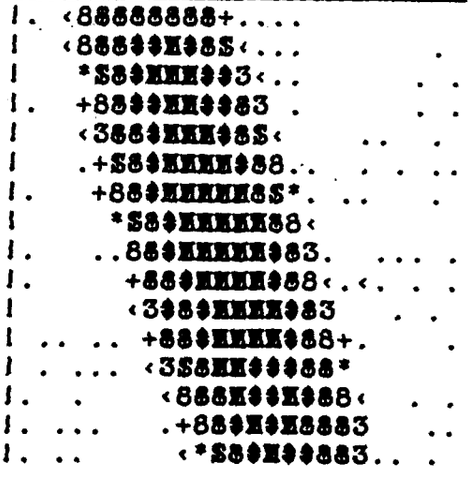
FSR = 0.2870
StdD = 0.3109



NOISELESS

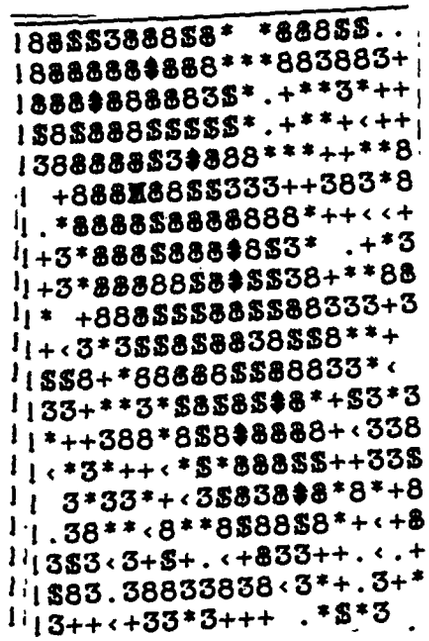


1st RECURSION

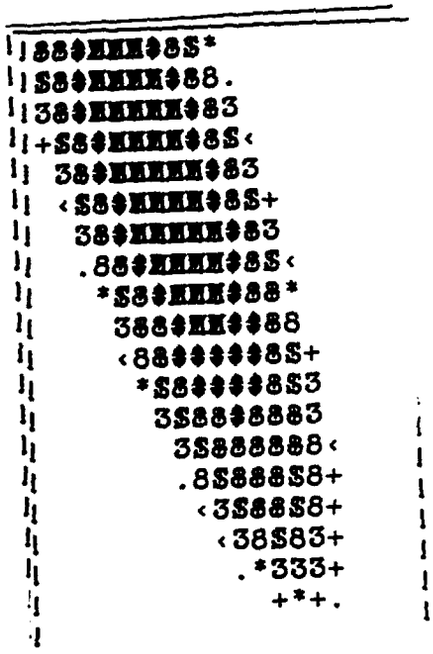


2nd RECURSION

SET 14 - ABSOLUTE
400-pixel

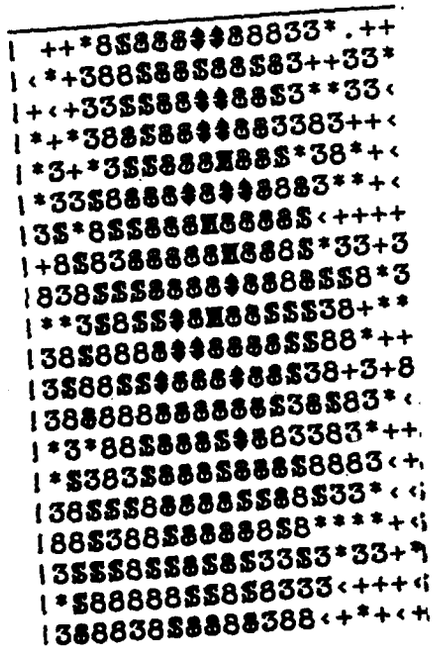


NOISY

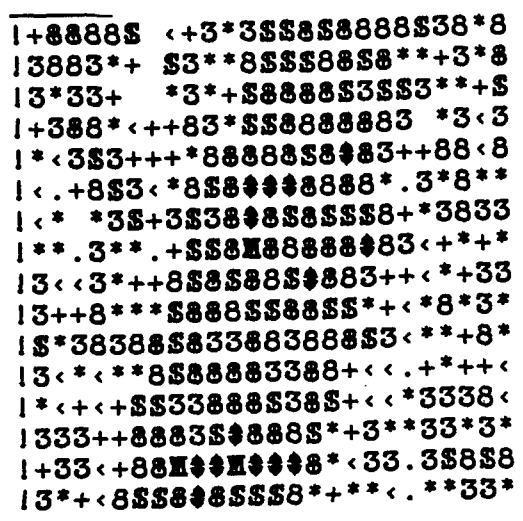


NOISELESS

FSR = 0.5263
StdD = 0.0764

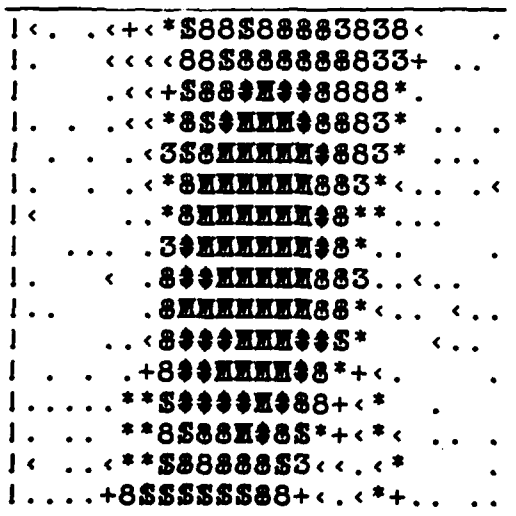


PROPAGATED



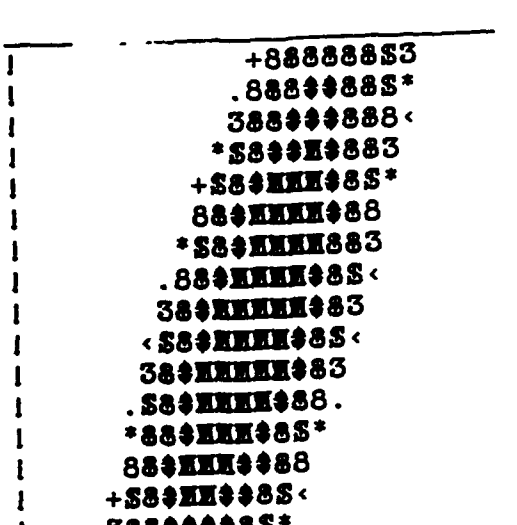
NOISE

FSR = 0.6461
StdD = 0.3146

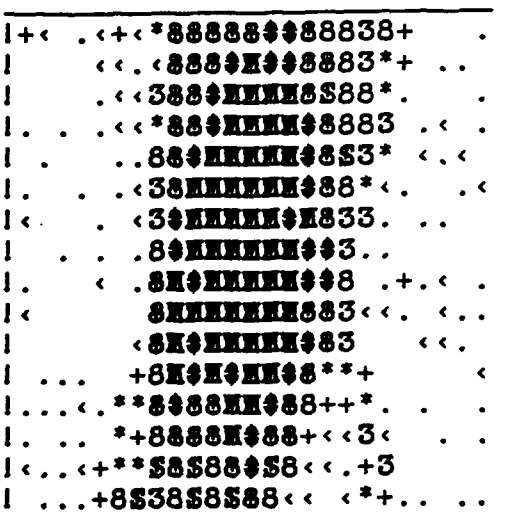


PROPAGATED

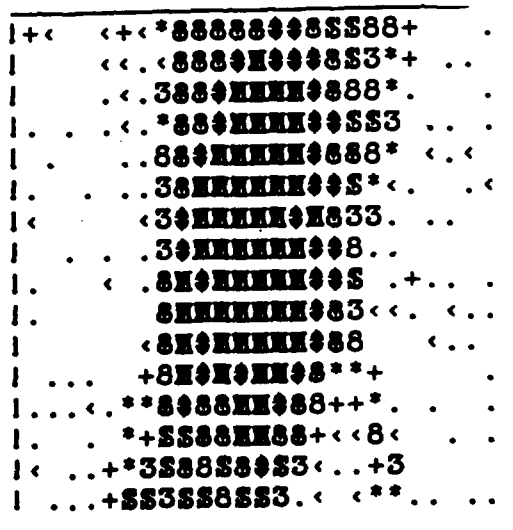
FSR = 0.3341
StdD = 0.3146



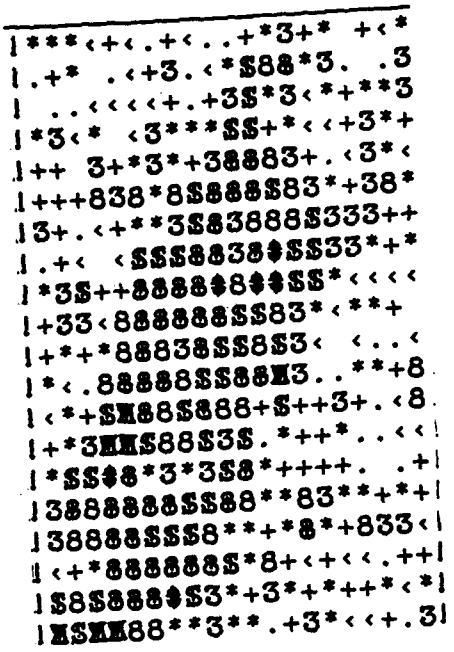
NOISELESS



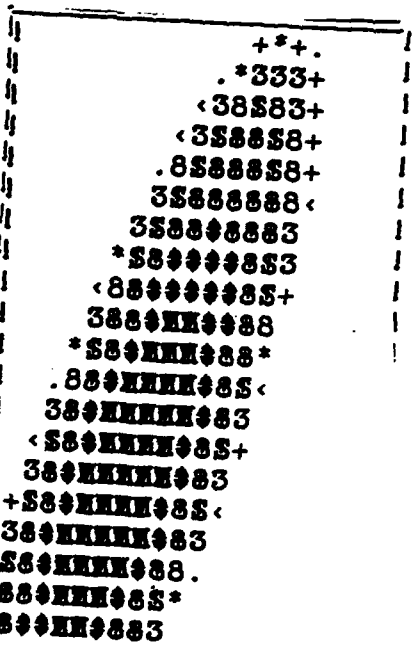
1st RECURSION



2nd RECURSION



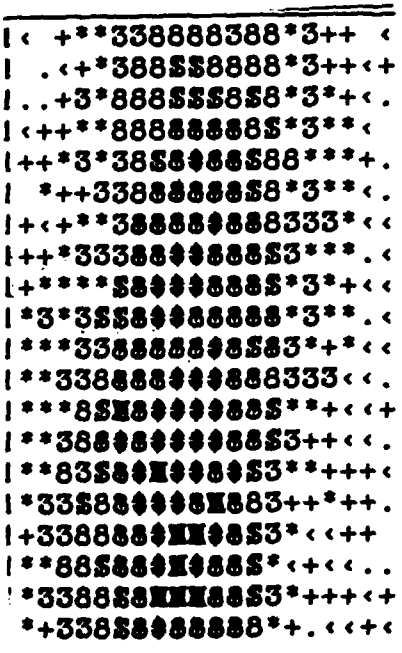
NOISE



NOISELESS

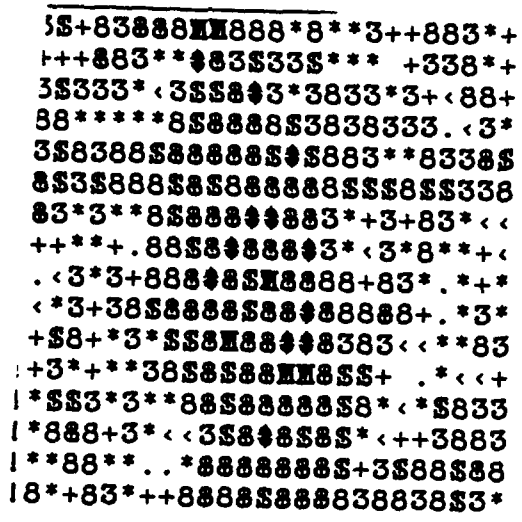
FSR = 0.4851

StdD = 0.0772



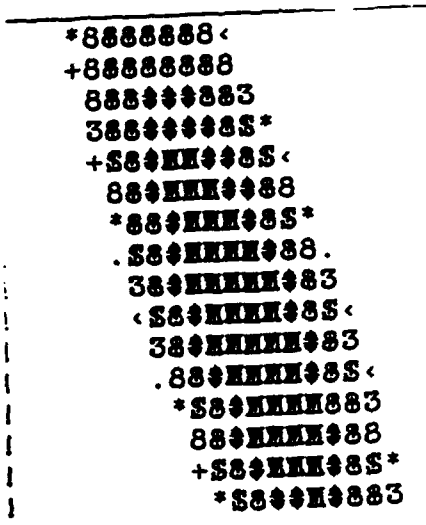
PROPAGATED

FSR = 1.0266

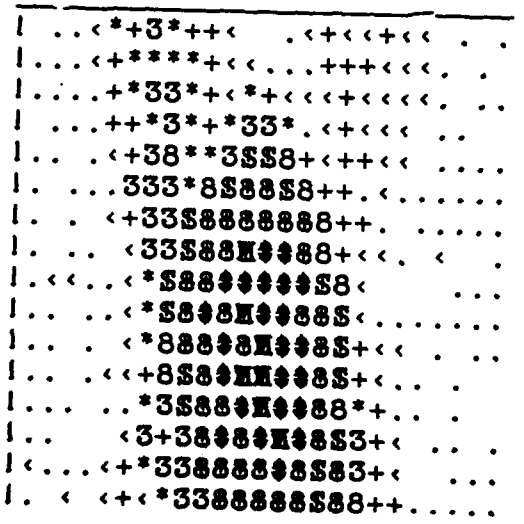


NOISY

FSR =0.6494
StdD = 0.3058

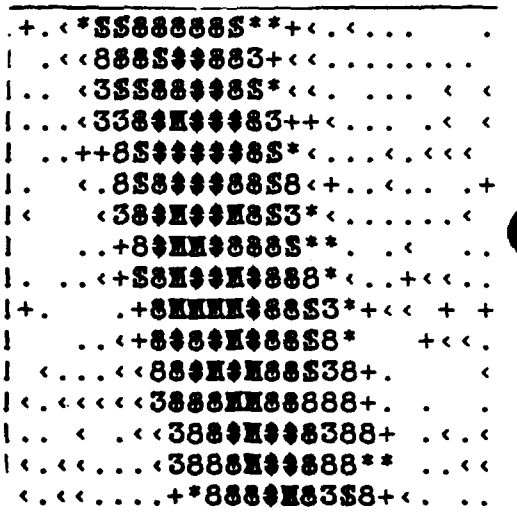


NOISELESS

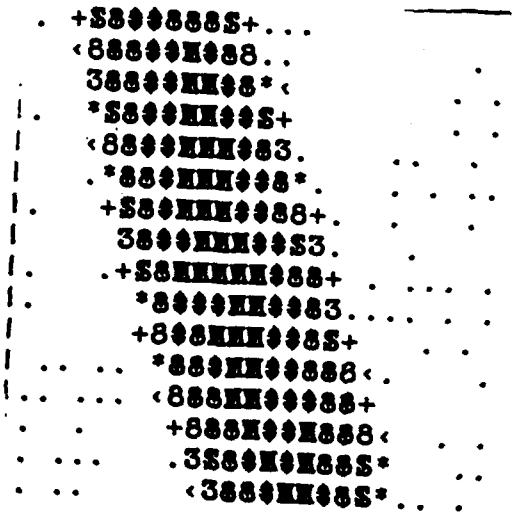


PROPAGATED

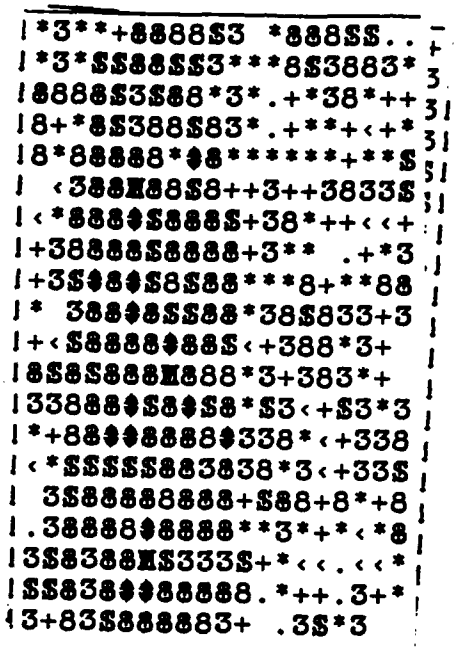
FSR = 0.4527
StdD = 0.3138



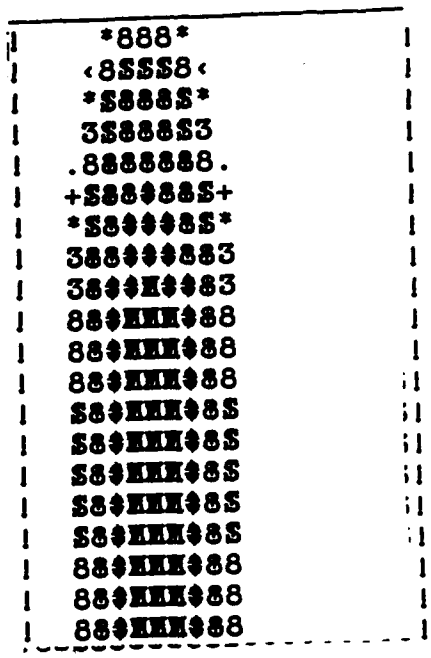
1st RECURSION



2nd RECURSION



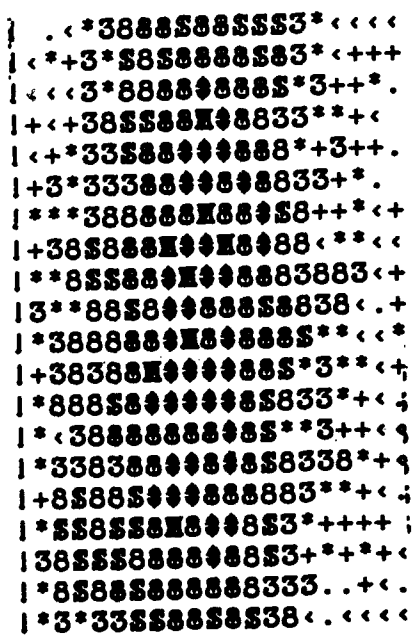
NOISE



NOISELESS

FSR = 0.5497

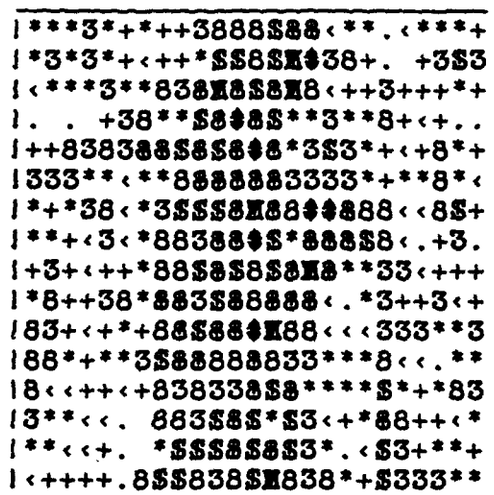
StdD = 0.0778



PROPAGATED

FSR = 0.5120

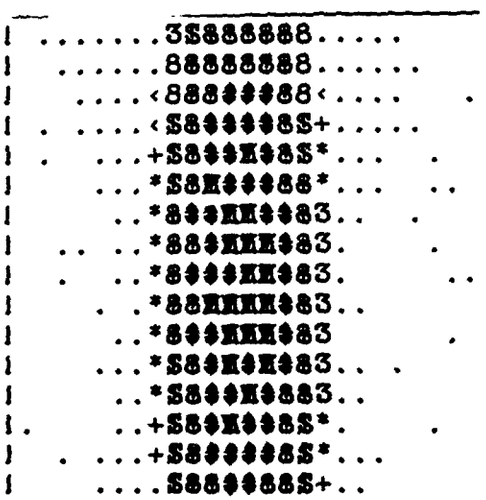
SET 16 - RELATIVE
400-Node, TRAINING SET



NOISY

FSR = 0.7044

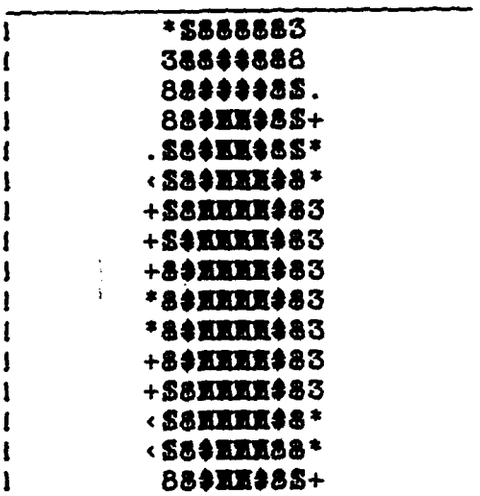
StdD = 0.03037



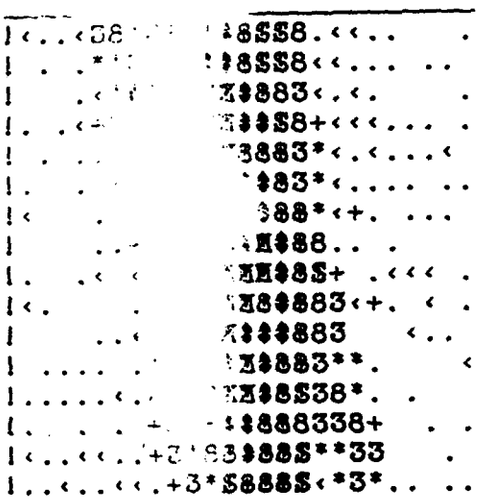
PROPAGATED

FSR = 0.1685

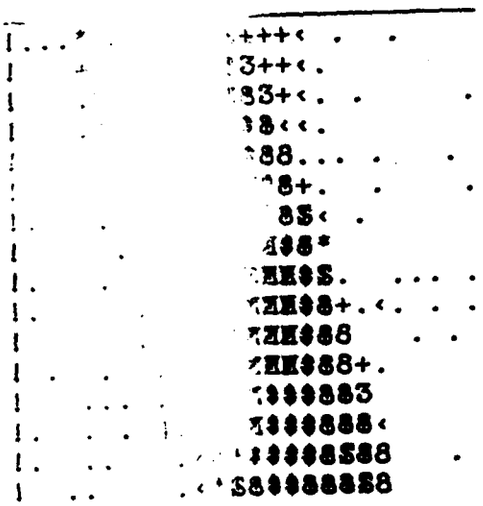
StdD = 0.3099



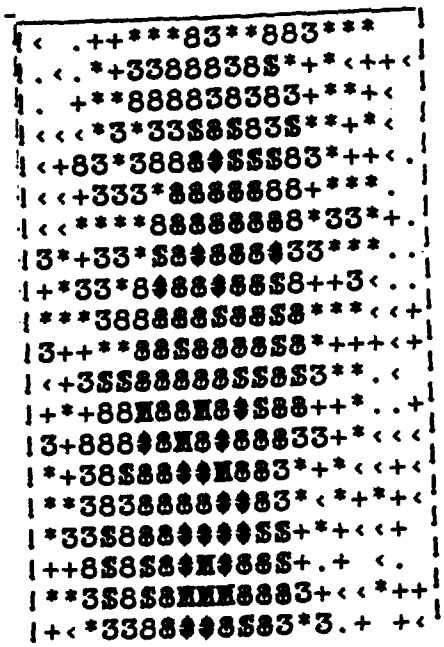
NOISELESS



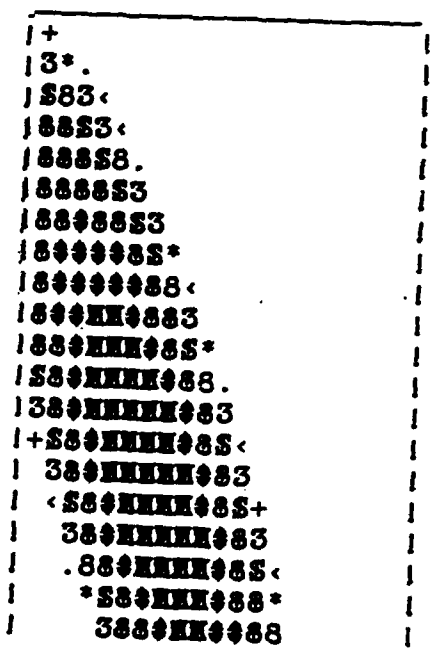
1st RECURSION



2nd RECURSION



NOISE



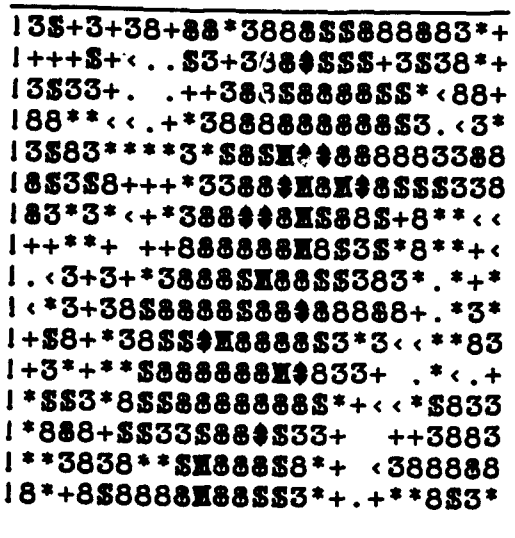
NOISELESS

FSR = 0.5484

StdD = 0.0783

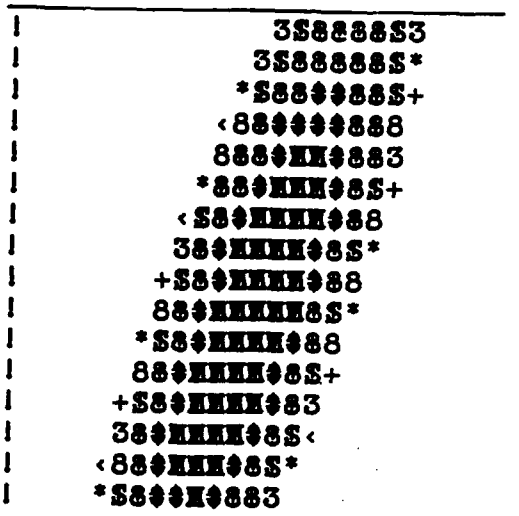
PROPAGATED

FSR = 0.7789

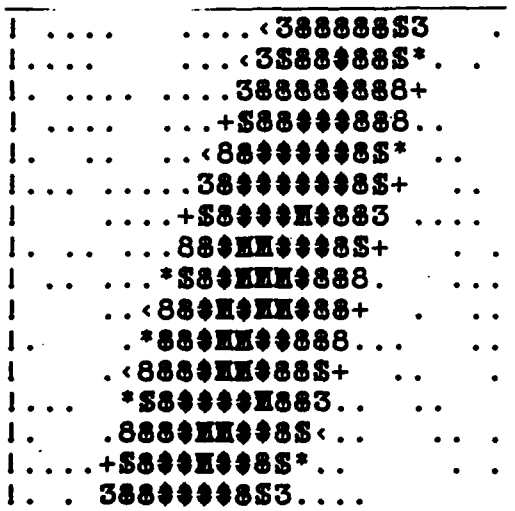


NOISE

FSR = 0.5164
StdD = 0.3057

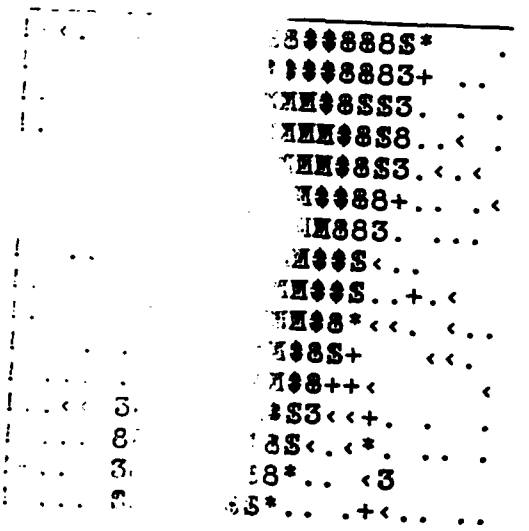


NOISELESS

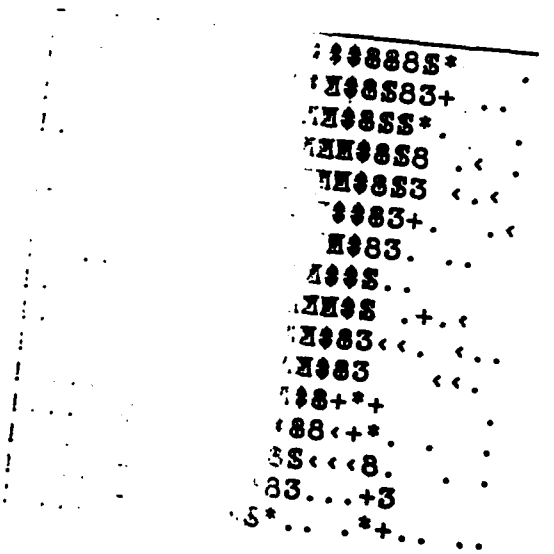


PROPAGATED

FSR = 0.1563
StdD = 0.3139

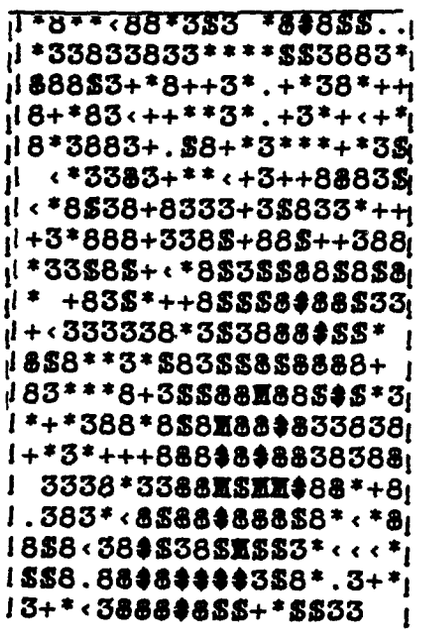


1st RECURSION

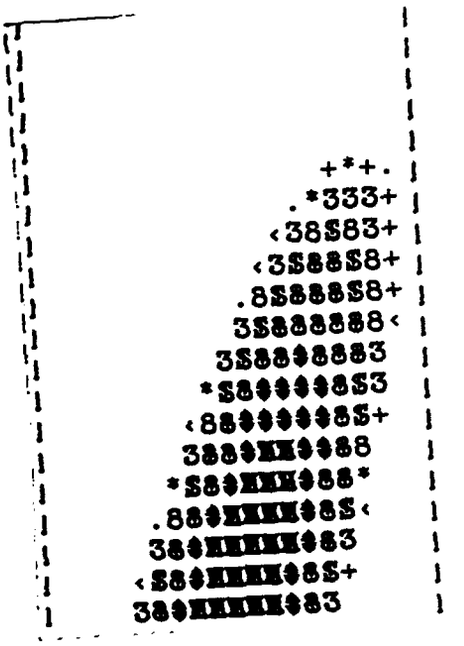


2nd RECURSION

SET 18 - ABSOLUTE
400-pixel



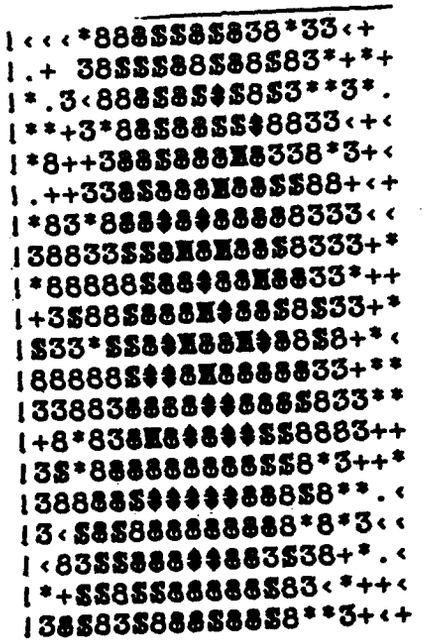
NOISY



NOISELESS

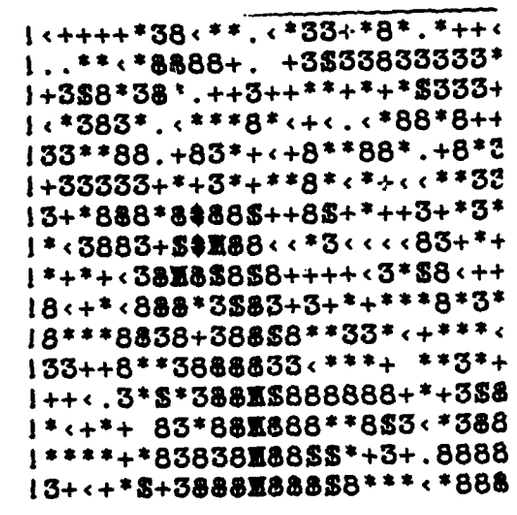
FSR = 0.6911

StdD = 0.0697



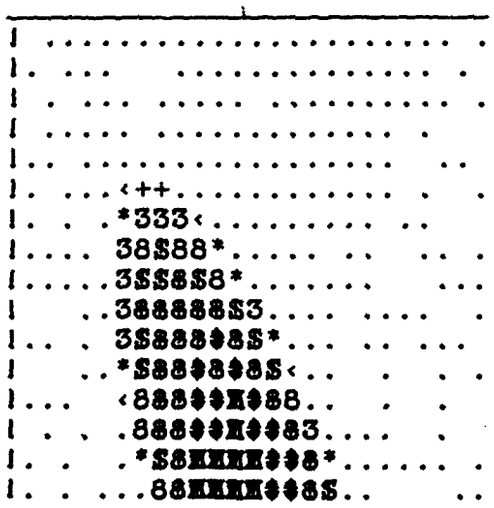
PROPAGATED

FSR = 1.1216



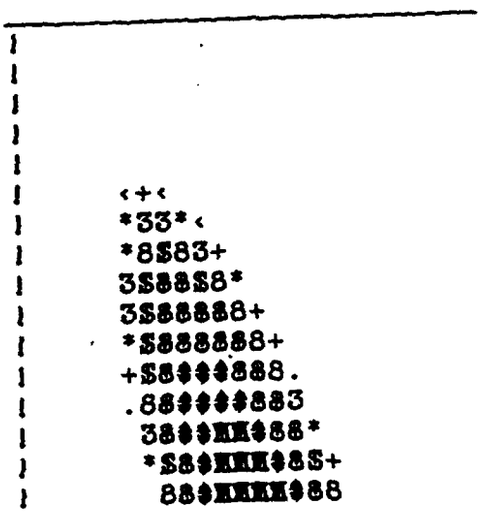
NOISE

FSR = 0.7808
StdD = 0.2578

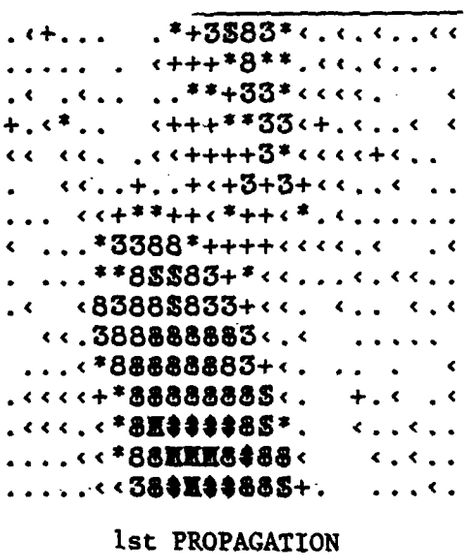


PROPAGATED

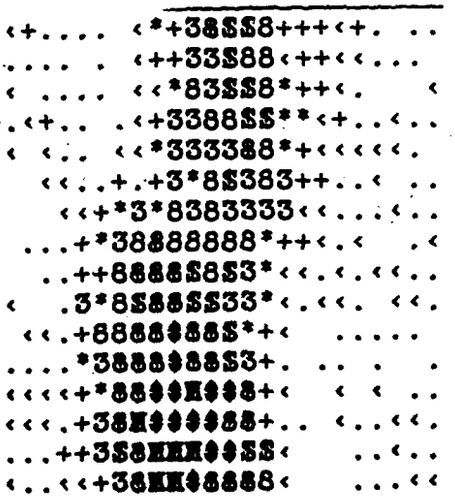
FSR = 0.3569
StdD = 0.2235



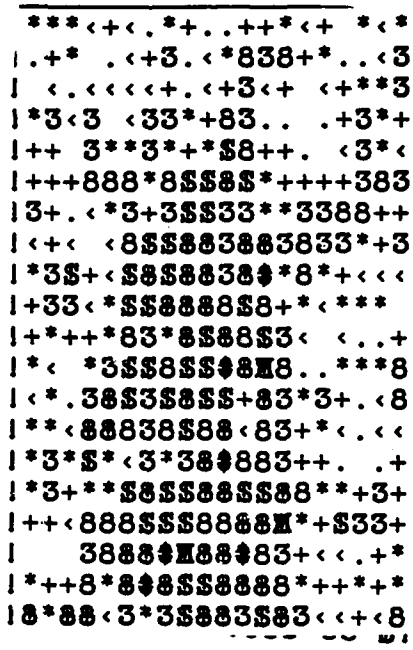
NOISLESS



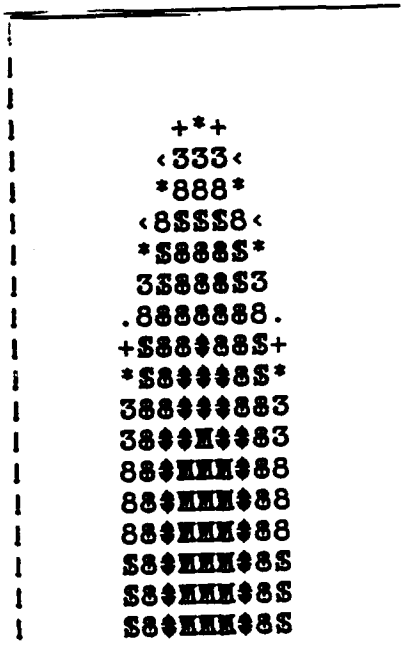
1st PROPAGATION



2nd PROPAGATION



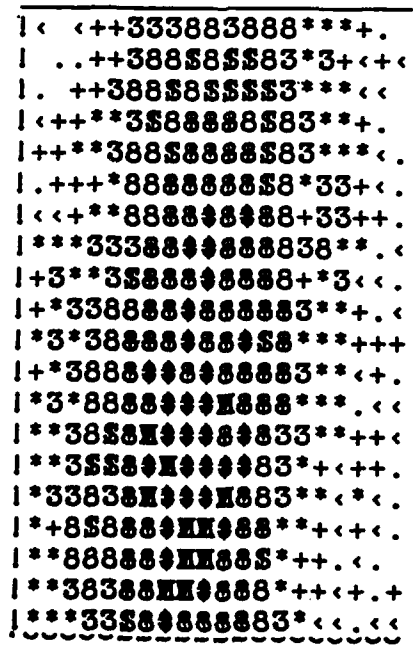
NOISE



NOISELESS

FSR = 0.6241

StdD = 0.0699



PROPAGATED

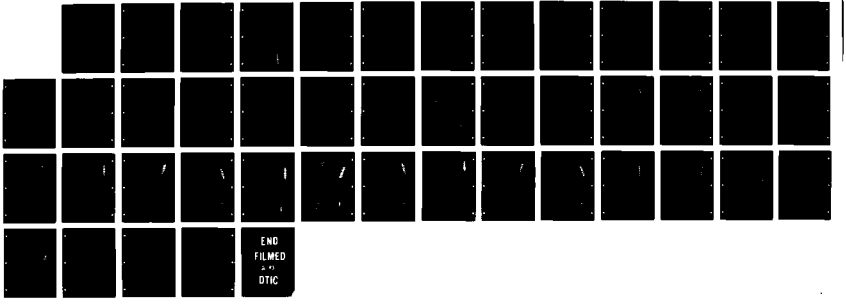
FSR = 1.3567

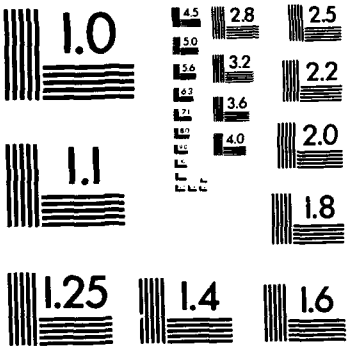
AD-A259 915 DEVELOPING A NEURAL NETWORK TO ACT AS A NOISE FILTER (U) ARMY ARMAMENT MUNITIONS AND CHEMICAL COMMAND ROCK ISLAND IL R RIVERO 2 OCT 92 AMCCOM-SA-R-9210 XA-AMCCOM

2/2

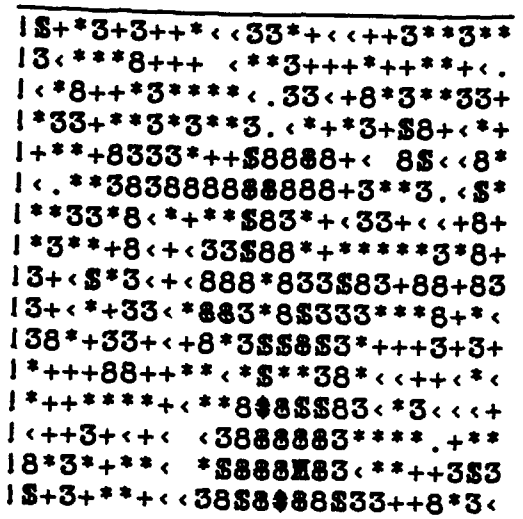
UNCLASSIFIED

NL



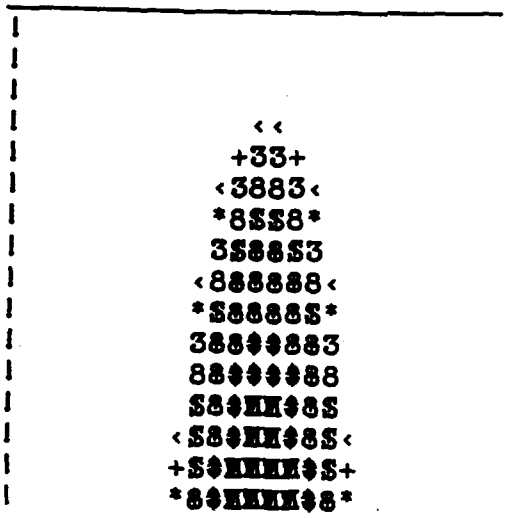

1.0
1.1
1.25
1.4
1.6
2.8
3.2
3.6
4.0
2.5
2.2
2.0
1.8

SET 19 - RELATIVE
400-Node, TRAINING SET

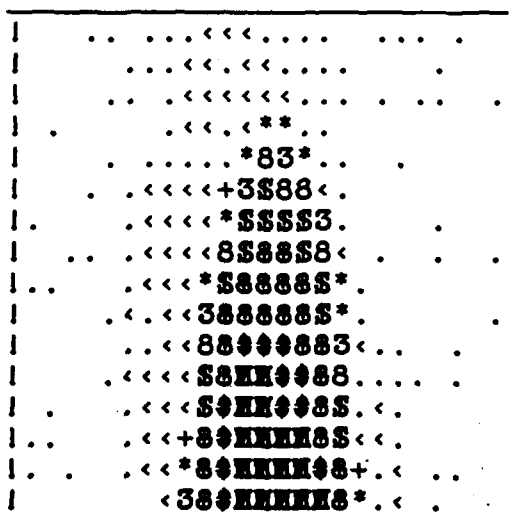


NOISE

FSR = 0.8003
StdD = 0.2578

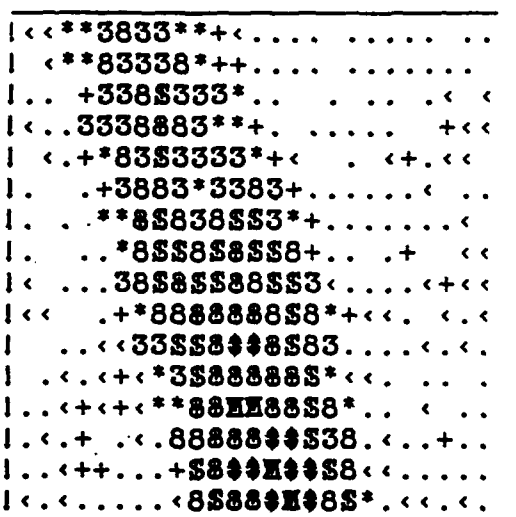


NOISELESS

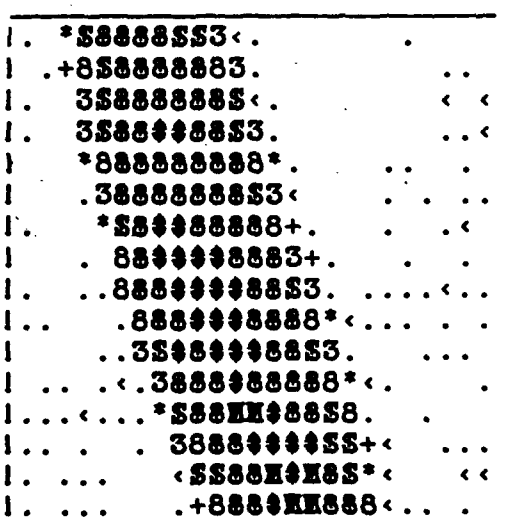


PROPAGATED

FSR = 0.3337
StdD = 0.2308



1st RECURSION

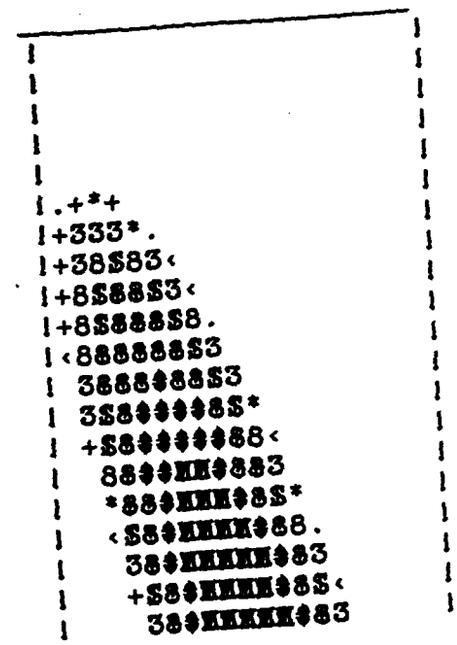


2nd RECURSION

SET 20 - ABSOLUTE
400 - PIXEL

TRAINING SET

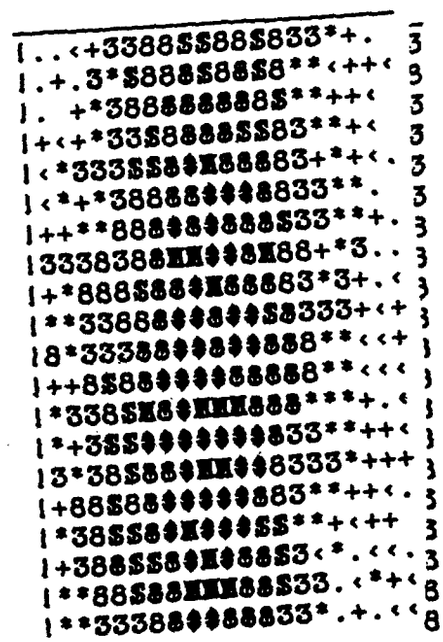
NOISY



NOISELESS

FSR = 0.6874

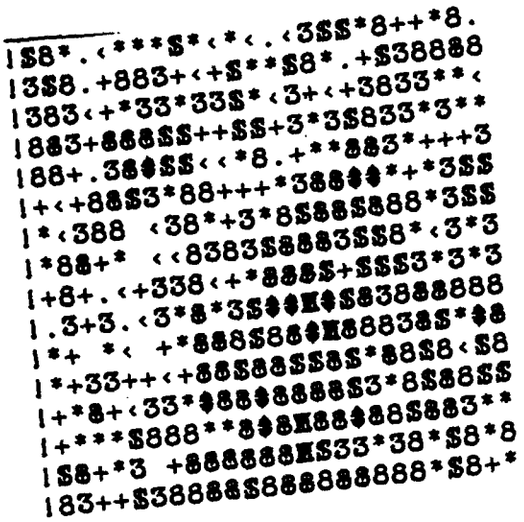
StdD = 0.0697



PROPAGATED

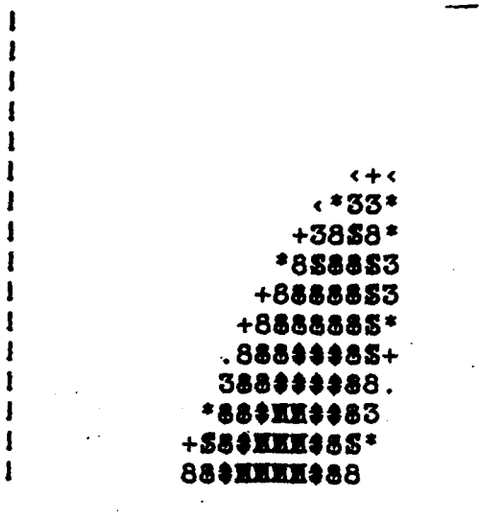
FSR = 0.3840

SET 20 - RELATIVE
400 - NODE, TRAINING SET

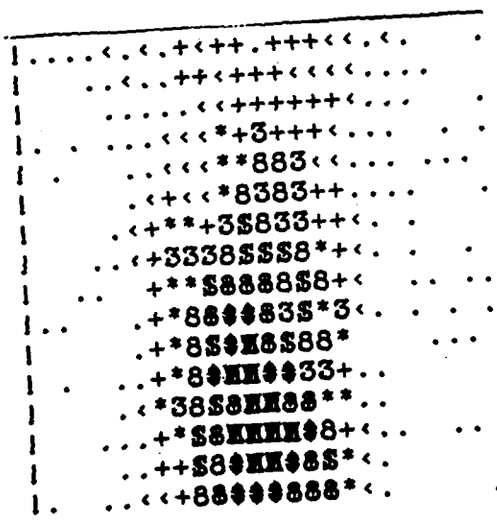


NOISE

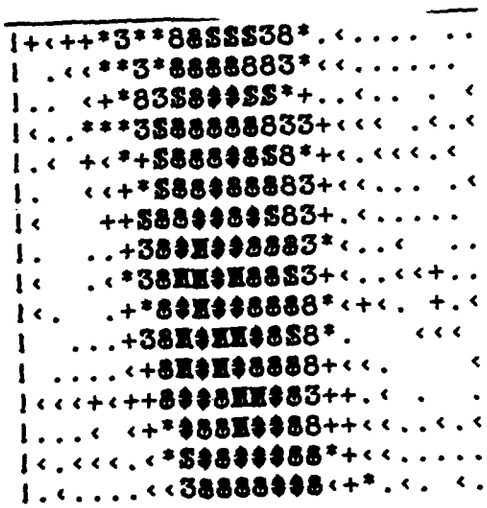
FSR = 1.0282
StdD= 0.2235



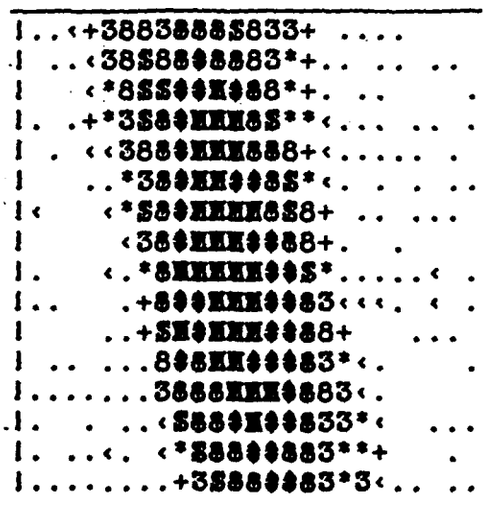
NOISELESS



PROPAGATED
FSR = 1.0758
StdD= 0.2235

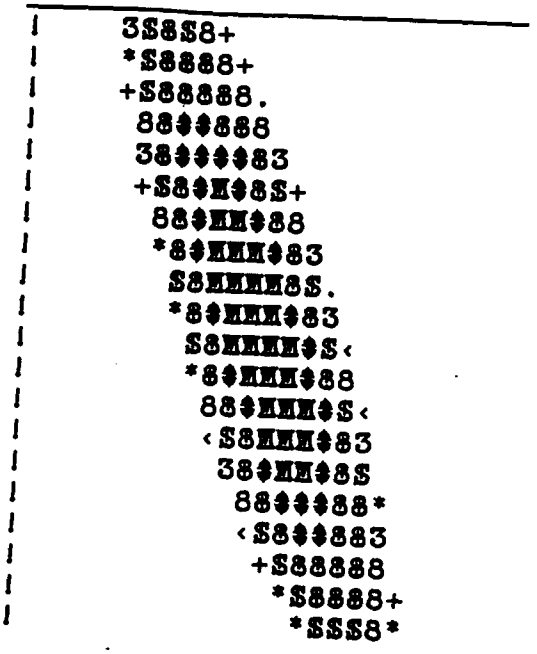


1st PROPAGATION

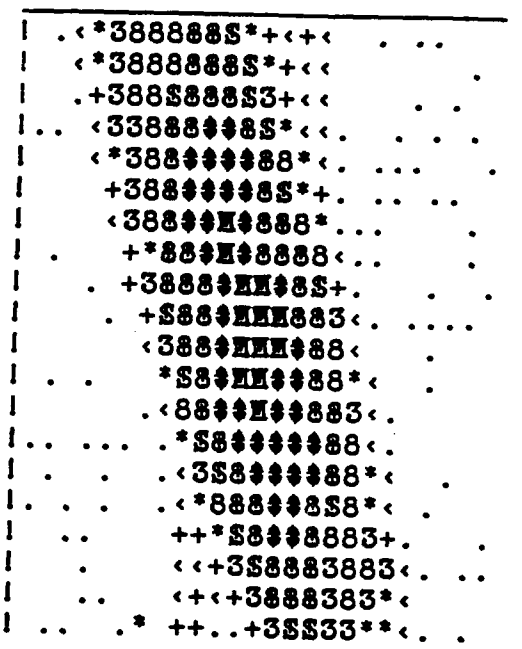


2nd PROPAGATION

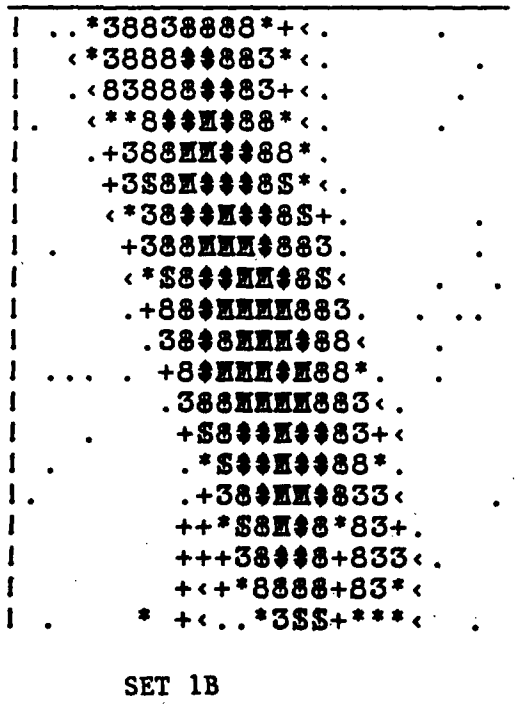
C.4.3. 500-pixel images



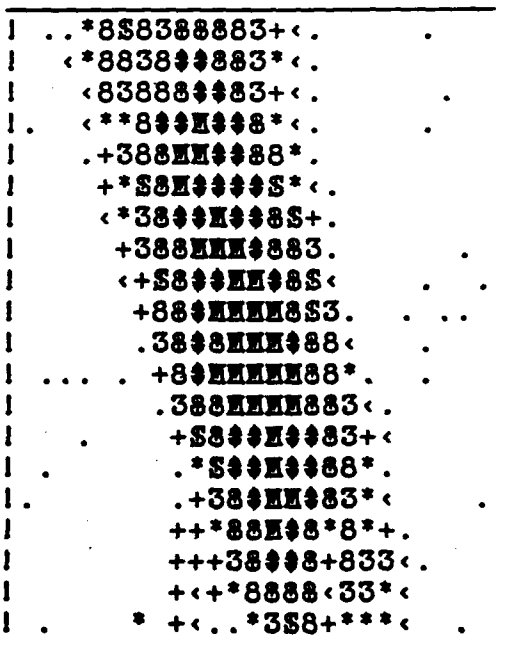
CLEAN



SET 1A

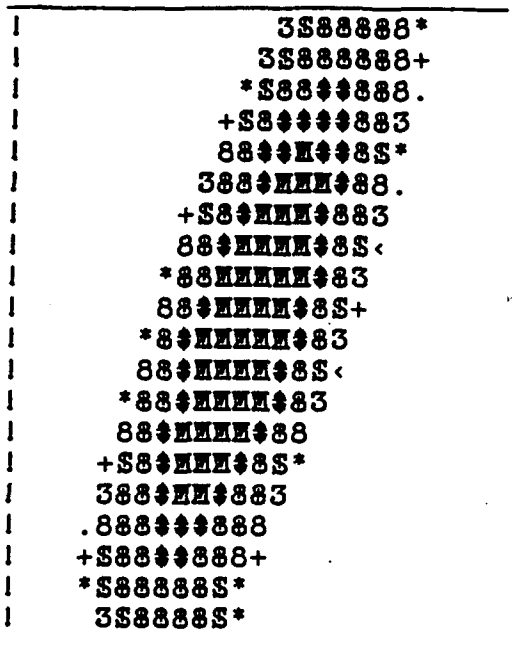


SET 1B

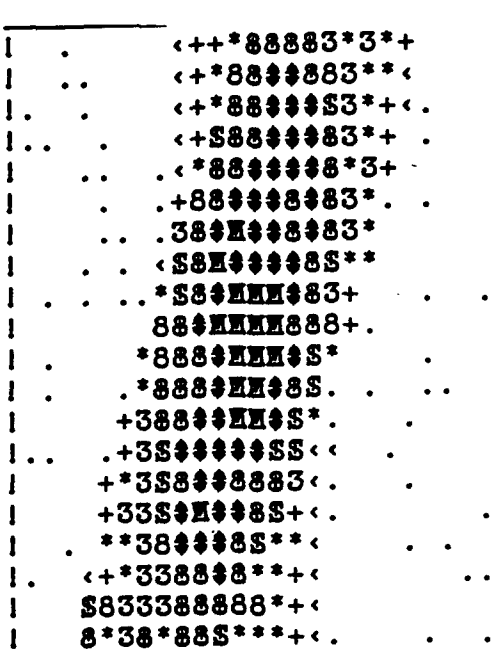


SET 1C

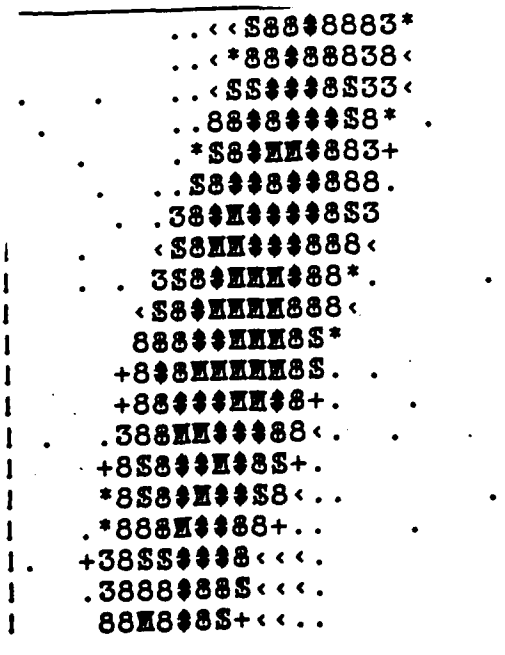
SET 2 - 500 - PIXEL SETS



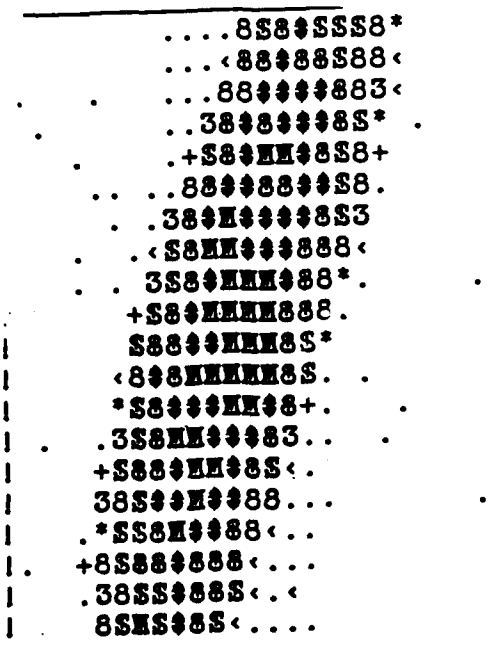
CLEAN



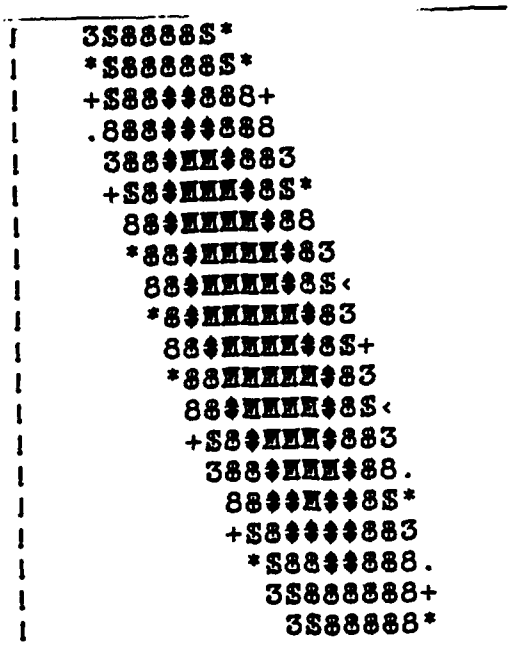
SET 2A



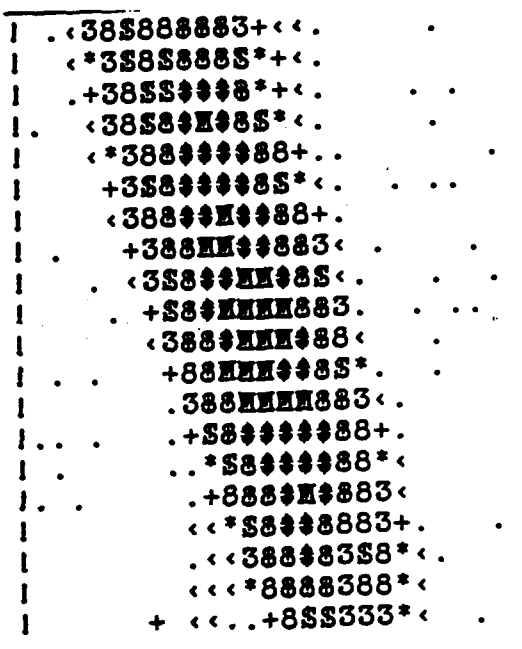
SET 2B



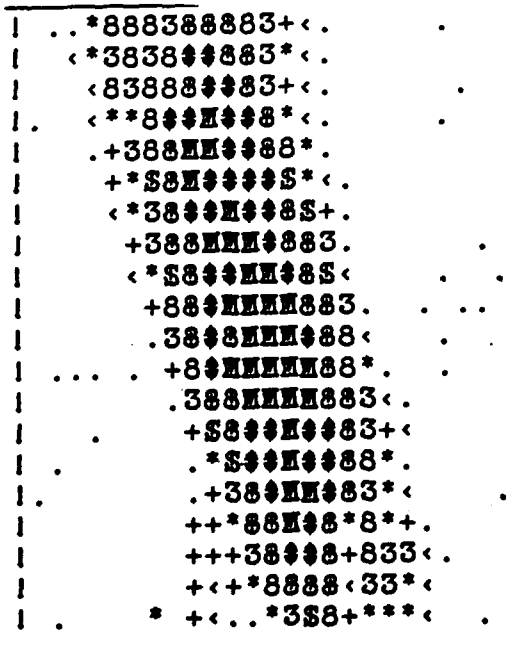
SET 2C



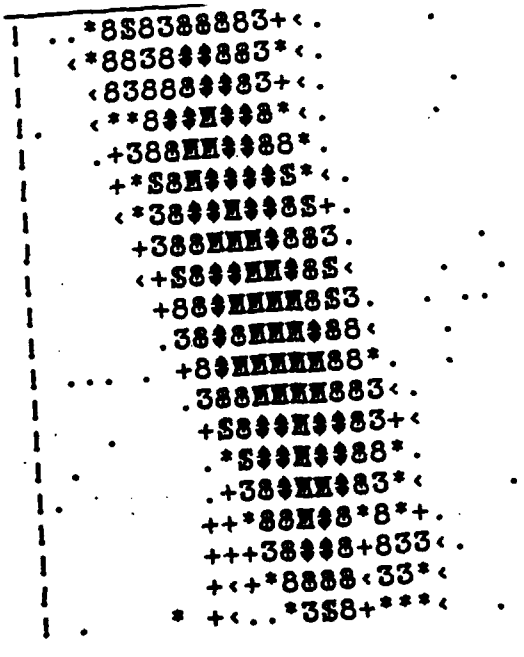
CLEAN



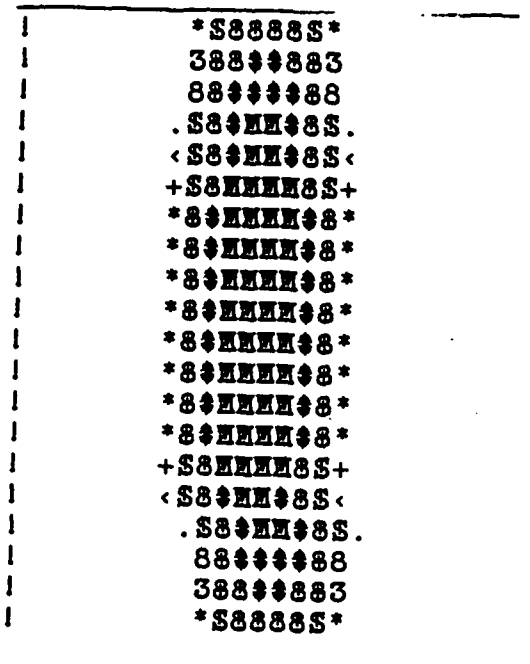
SET 3A



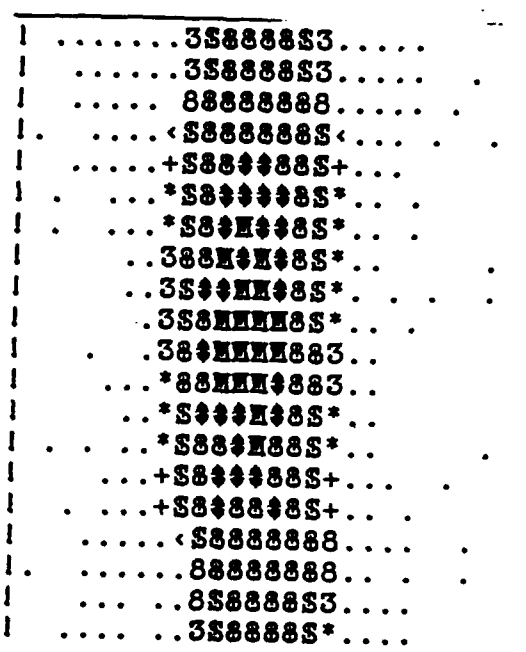
SET 3B



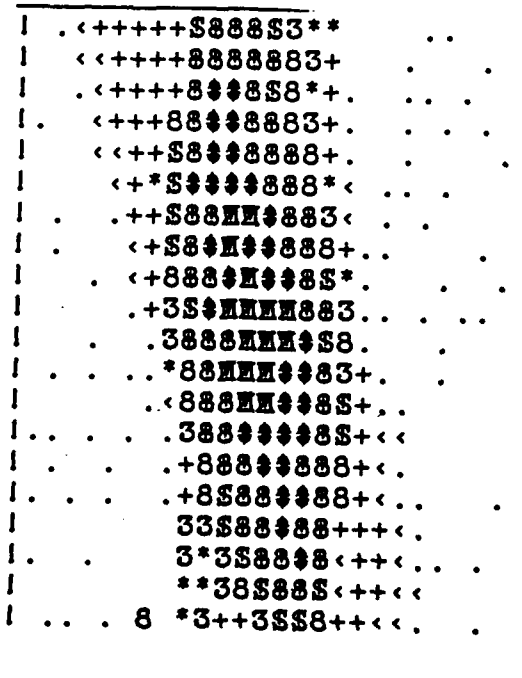
SET 3C



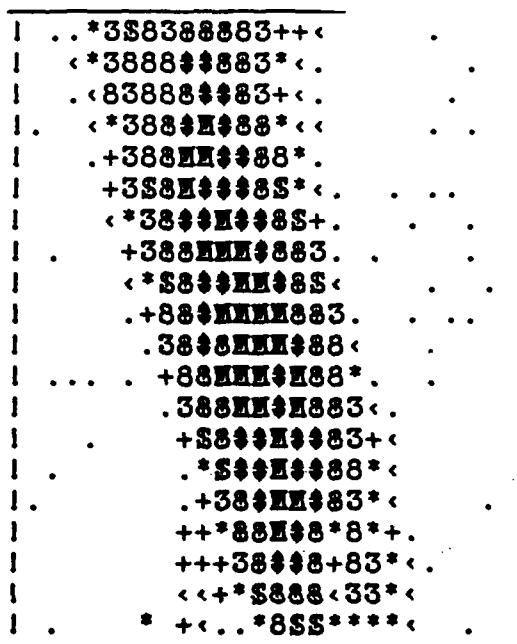
CLEAN



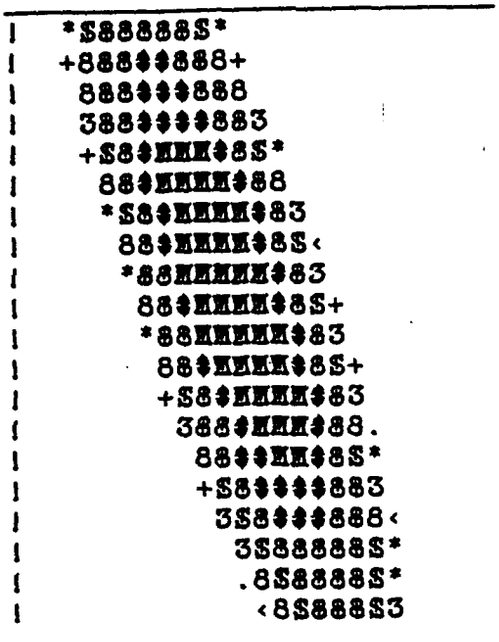
SET 5A



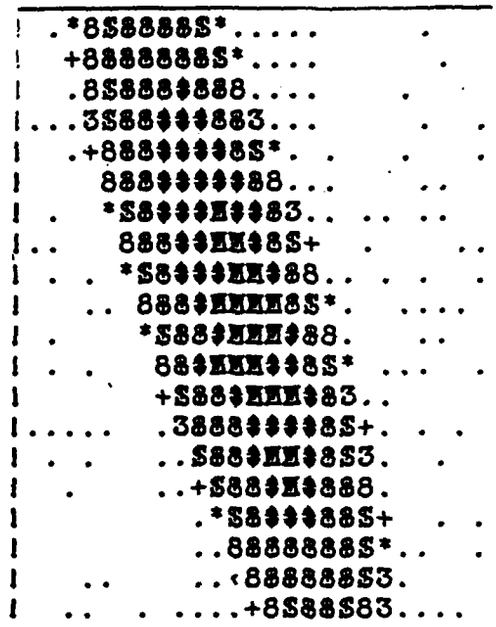
SET 5B



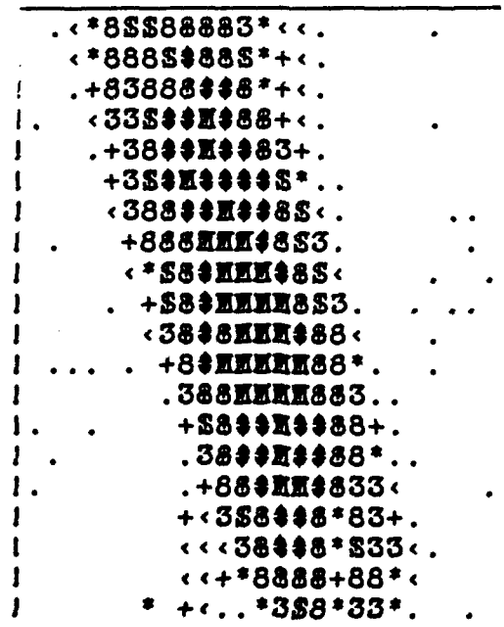
SET 5C



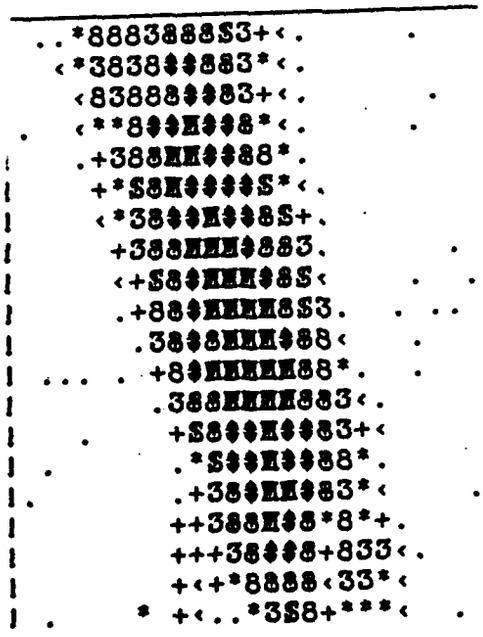
CLEAN



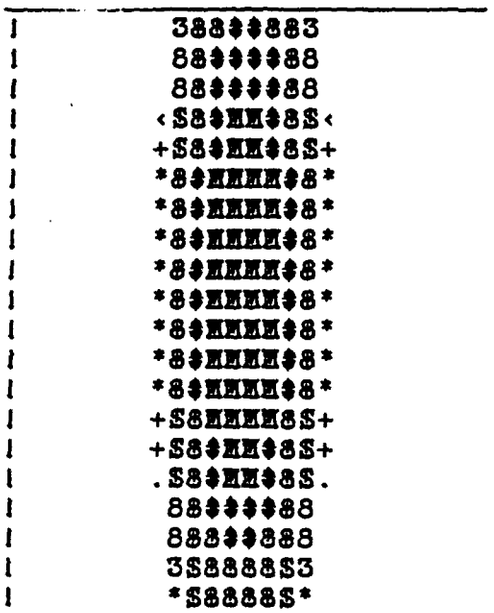
SET 6A



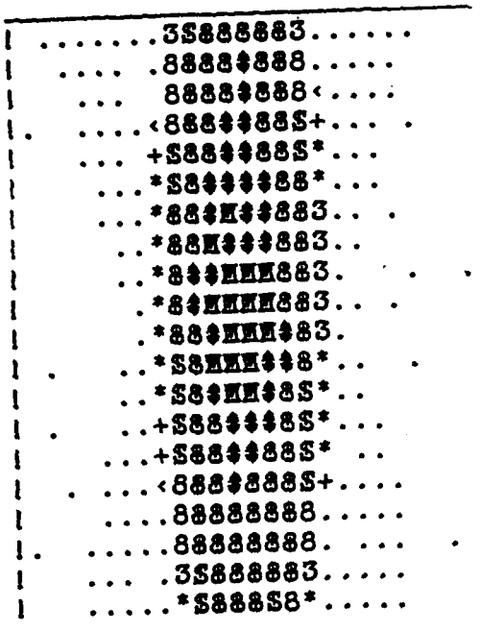
SET 6B



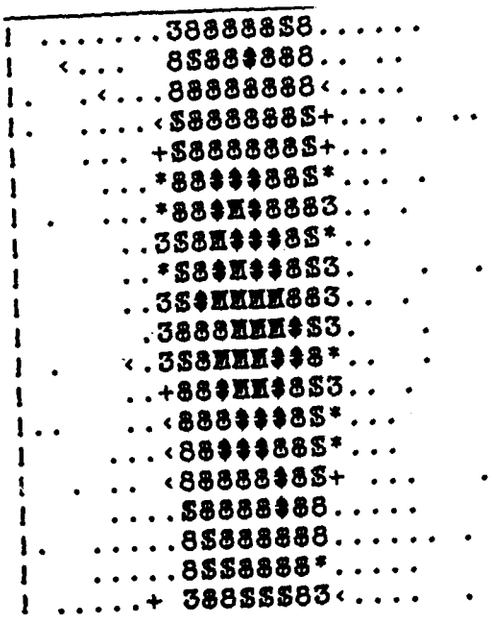
SET 6C



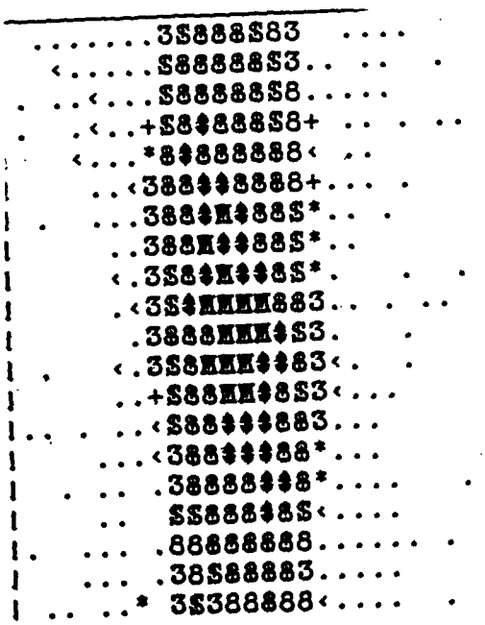
CLEAN



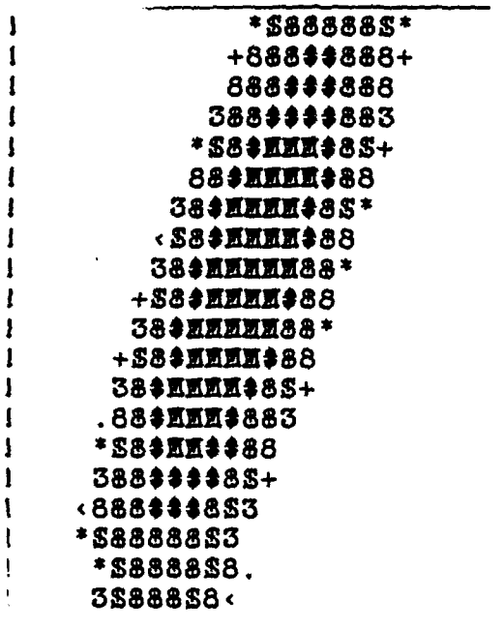
SET 7A



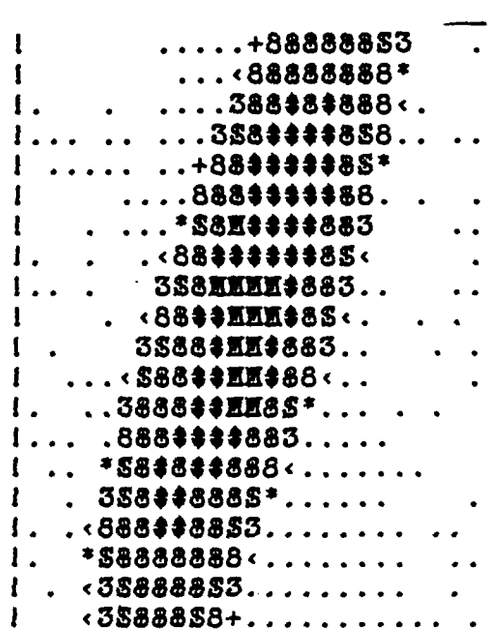
SET 7B



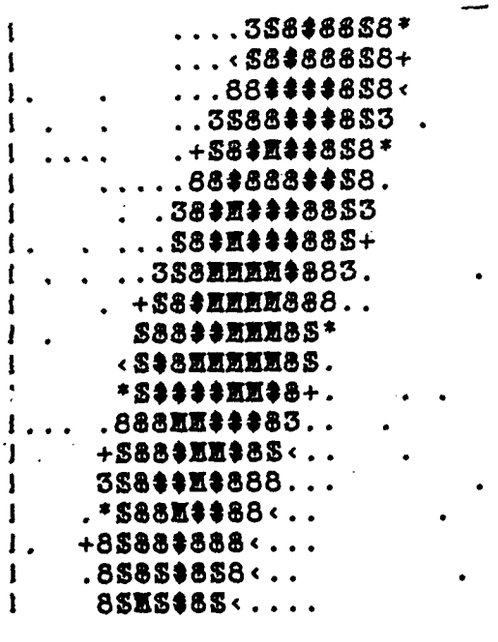
SET 7C



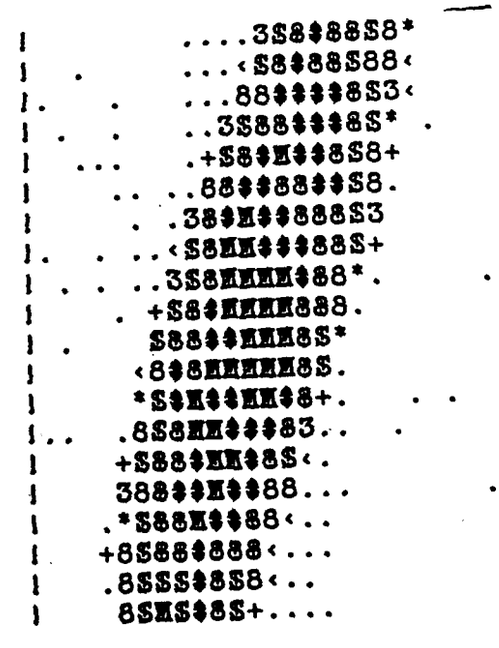
CLEAN



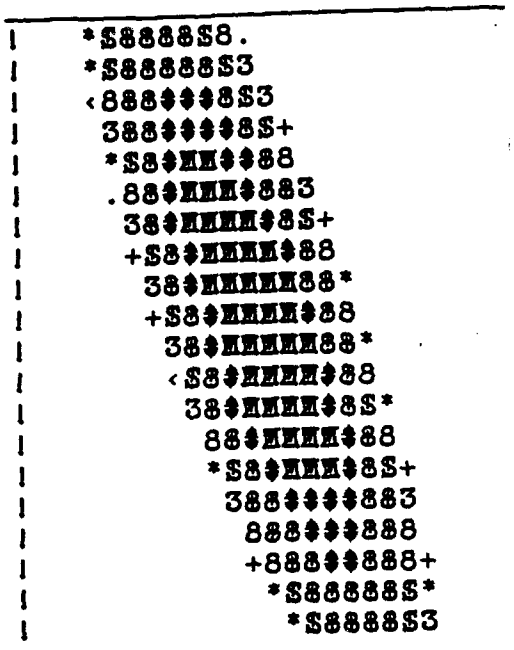
SET 8A



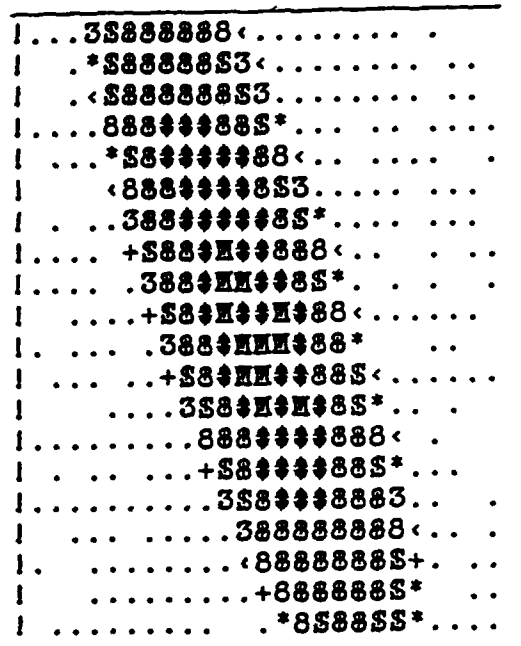
SET 8B



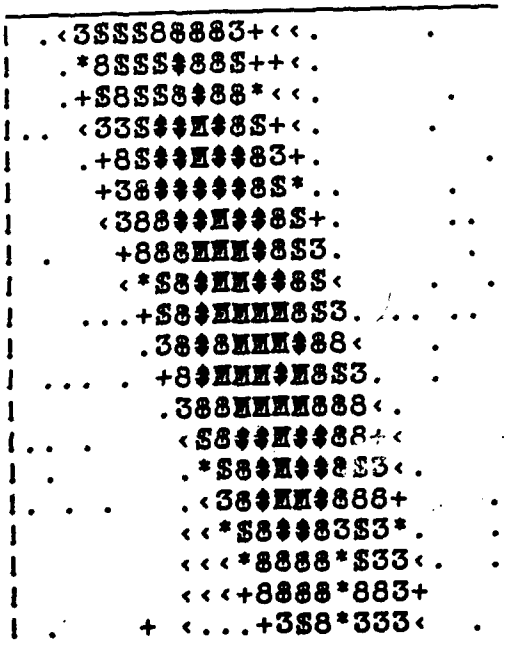
SET 8C



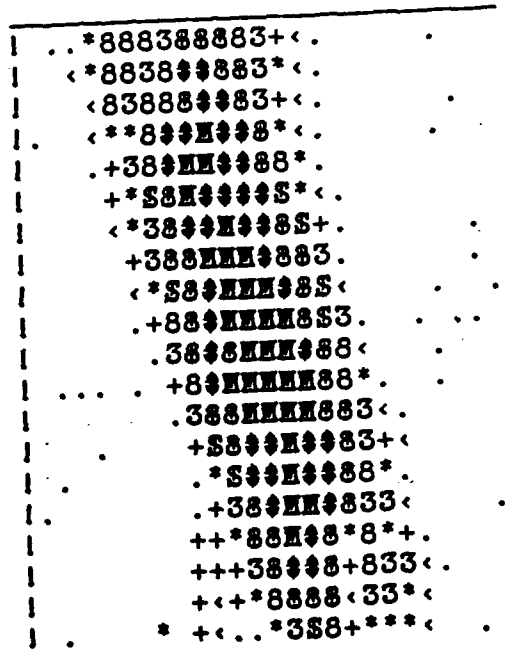
CLEAN



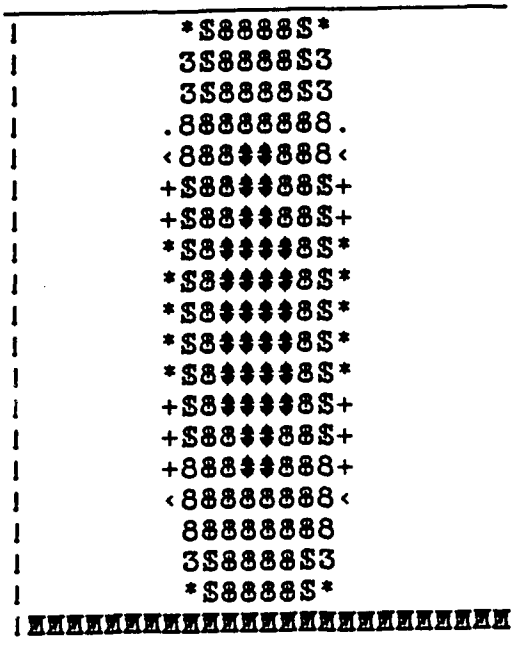
SET 9A



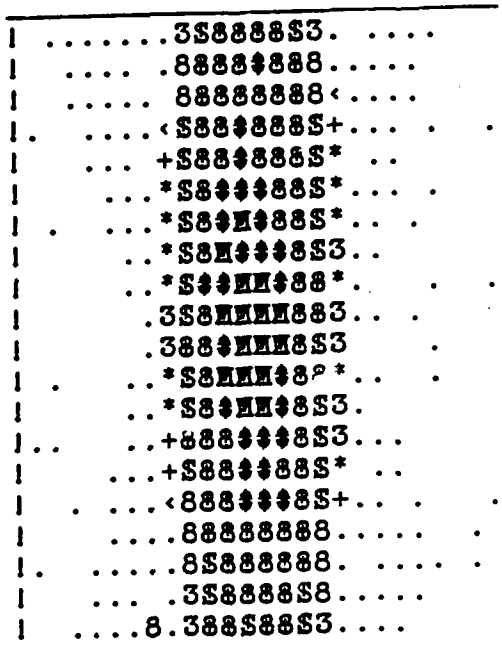
SET 9B



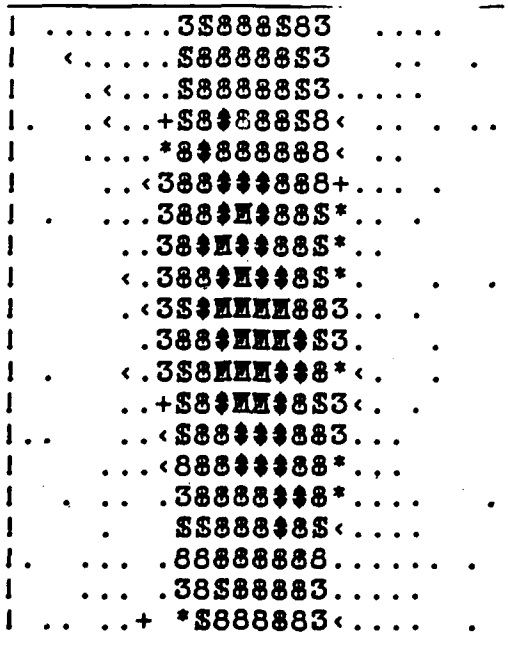
SET 9C



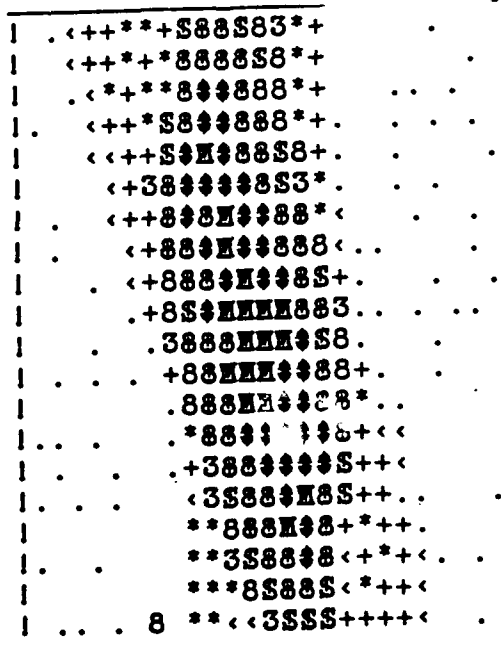
CLEAN



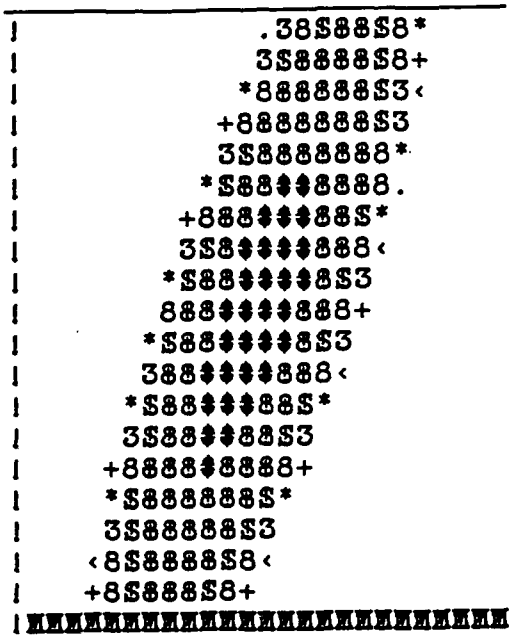
SET 10A



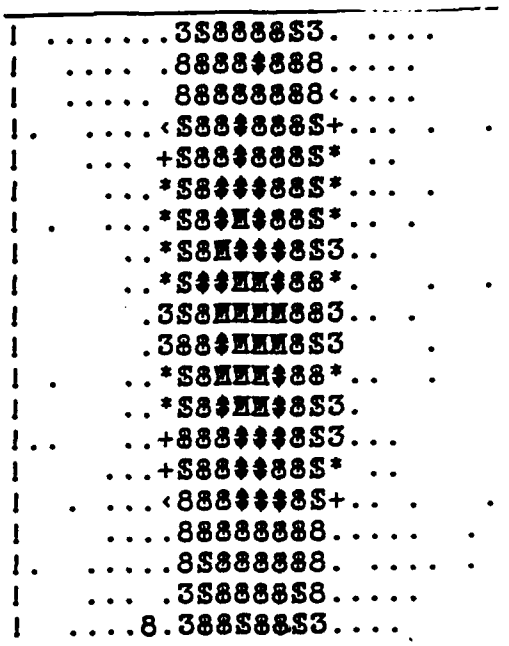
SET 10B



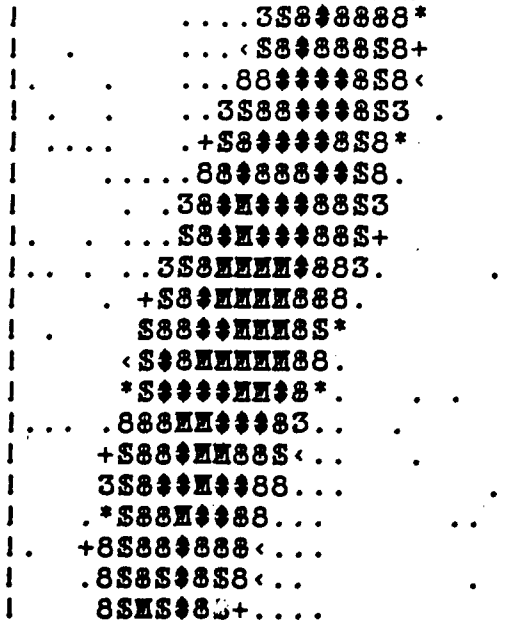
SET 10C



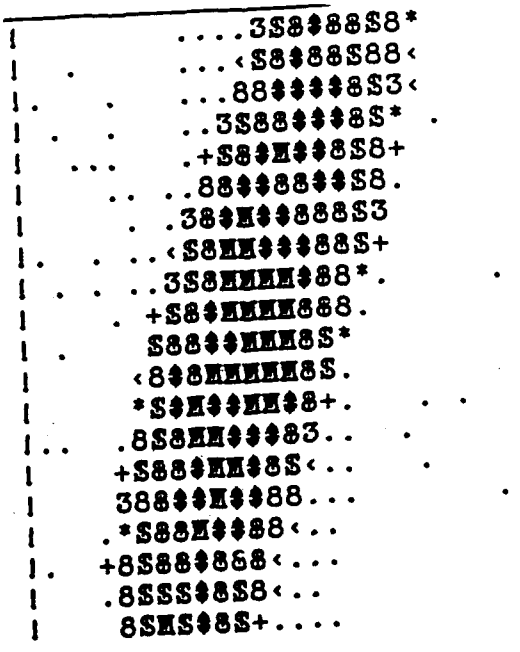
CLEAN



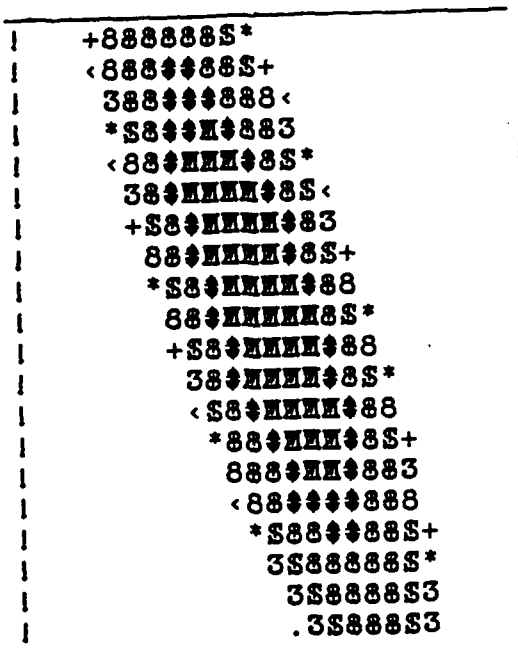
SET 11A



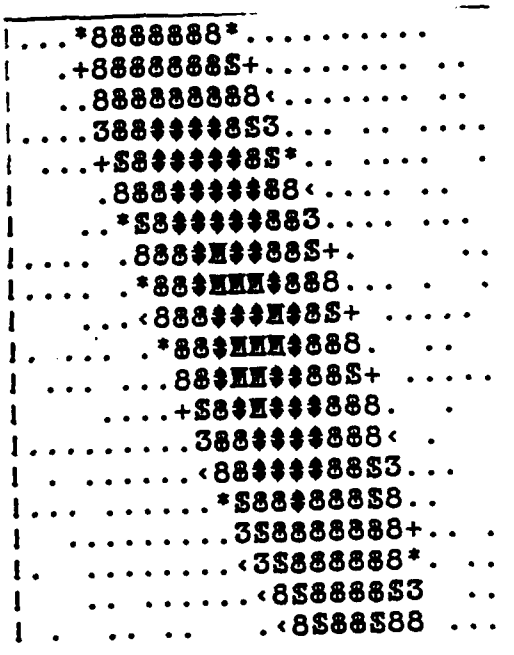
SET 11B



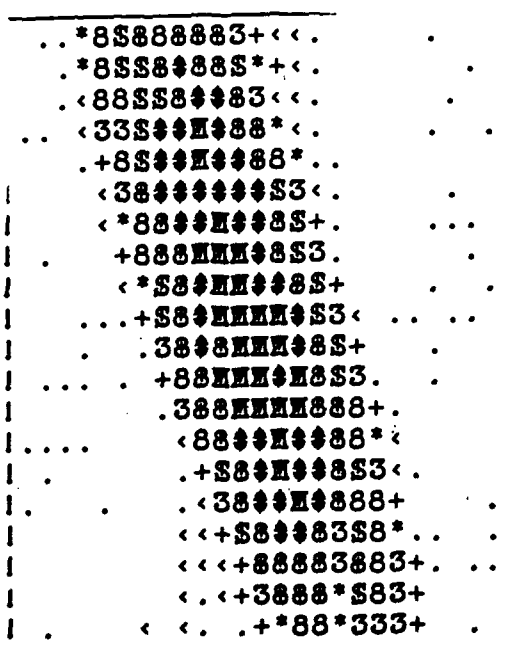
SET 11C



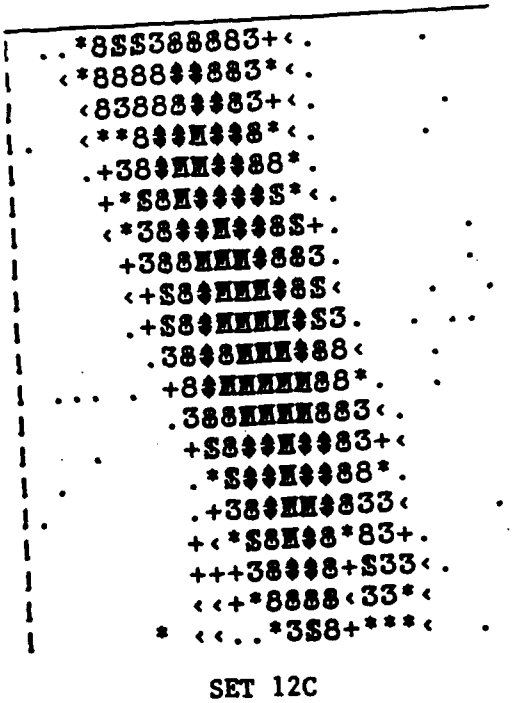
CLEAN



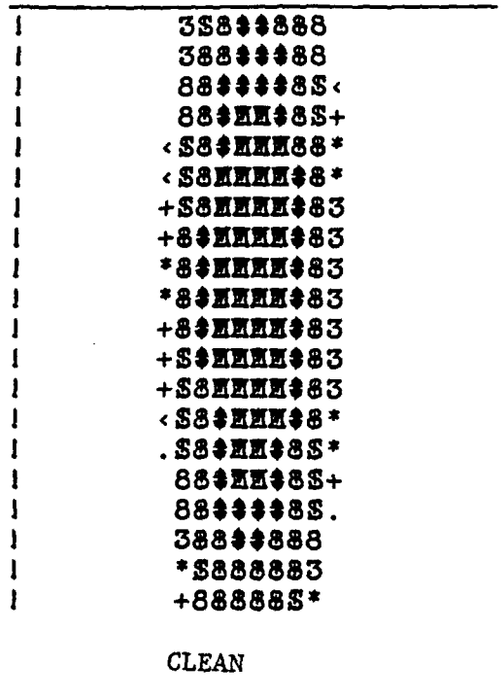
SET 12A



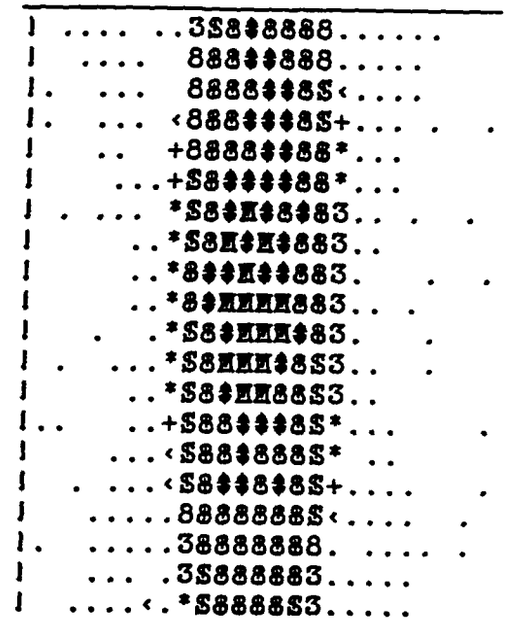
SET 12B



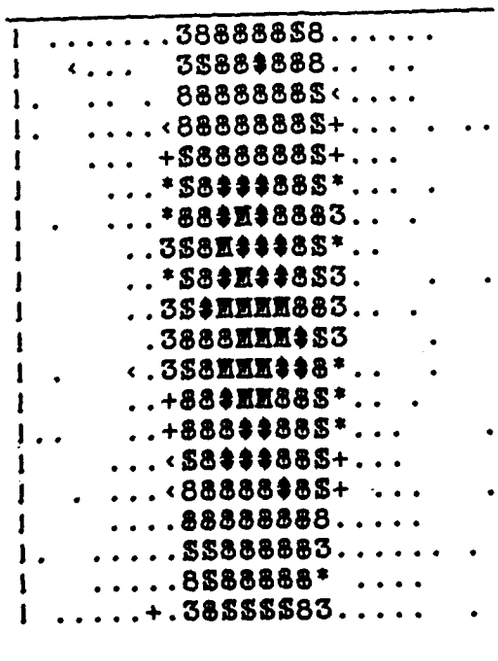
SET 12C



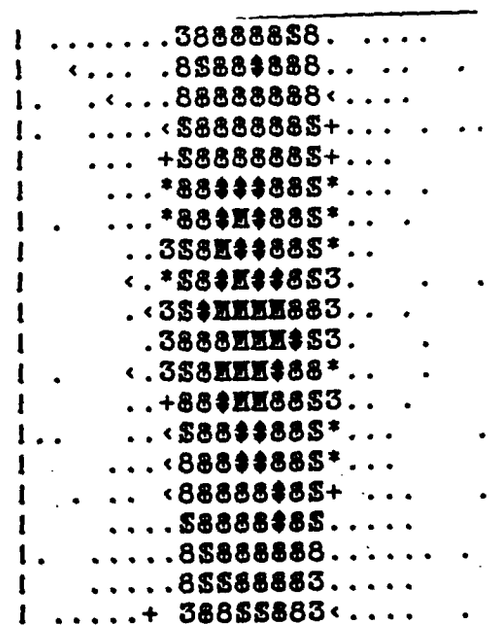
CLEAN



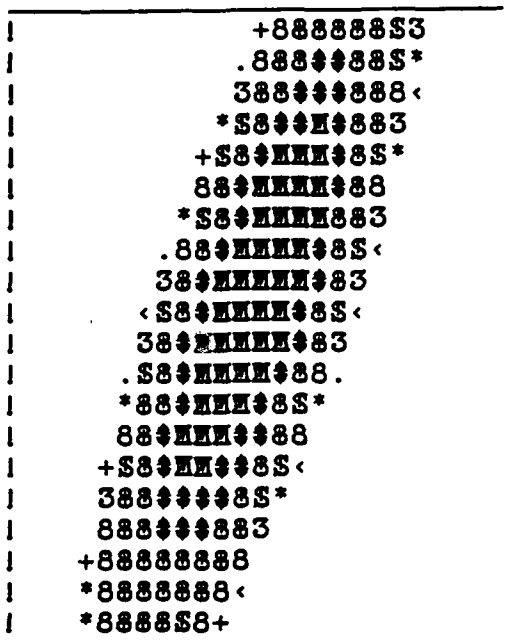
SET 13A



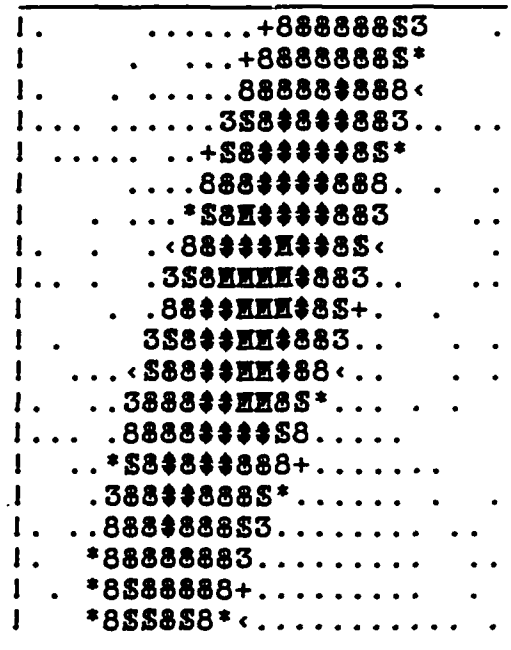
SET 13B



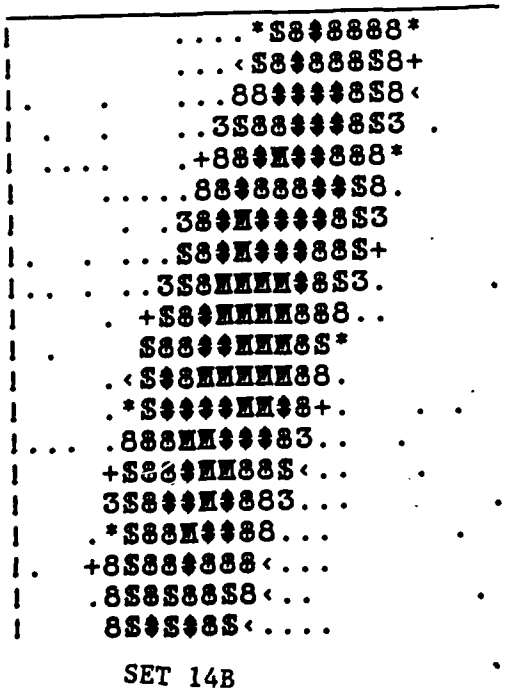
SET 13C



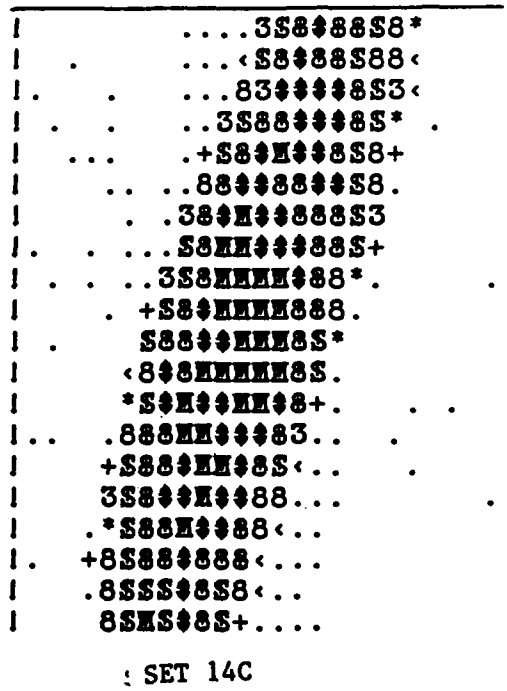
CLEAN



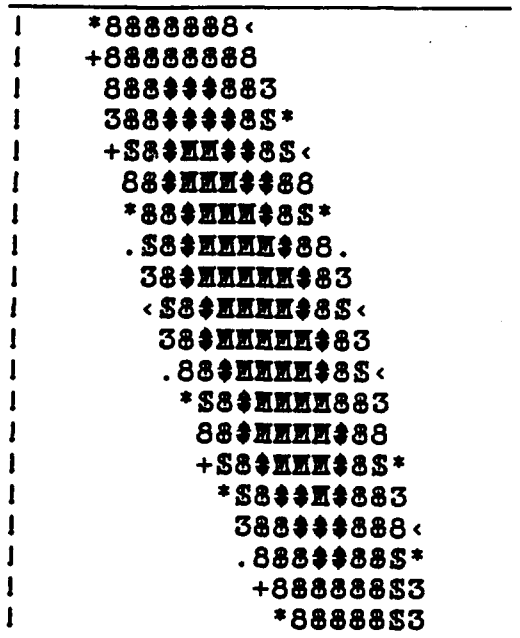
SET 14A



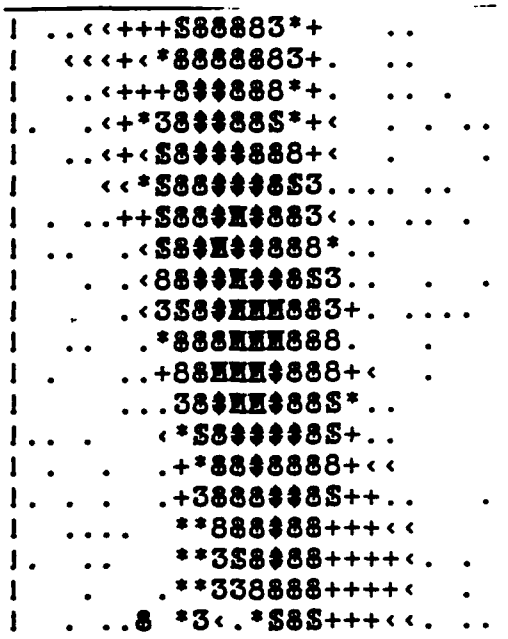
SET 14B



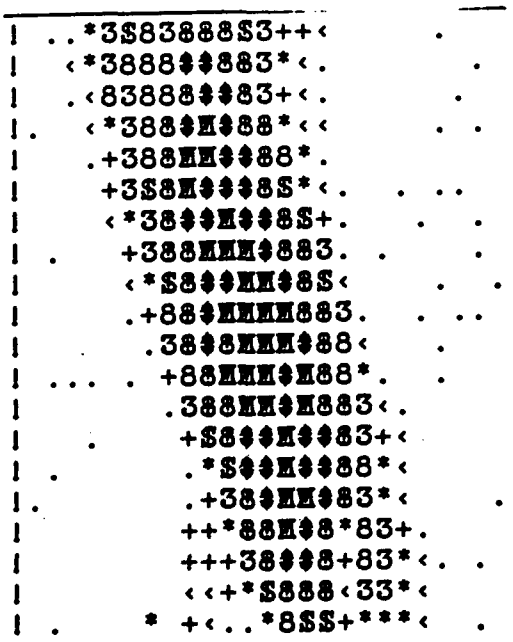
SET 14C



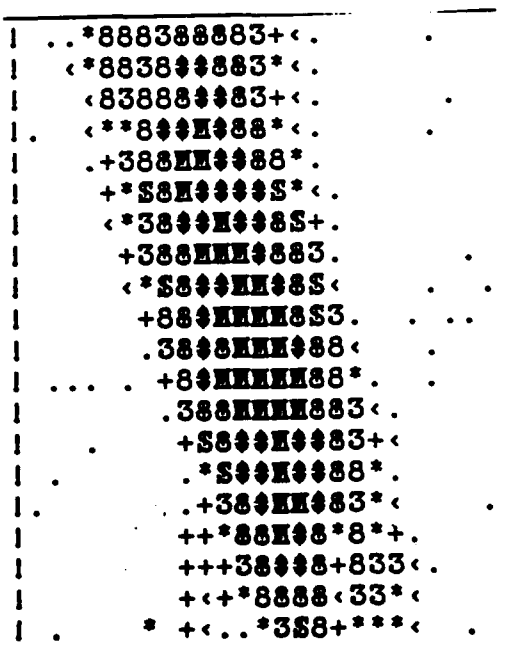
CLEAN



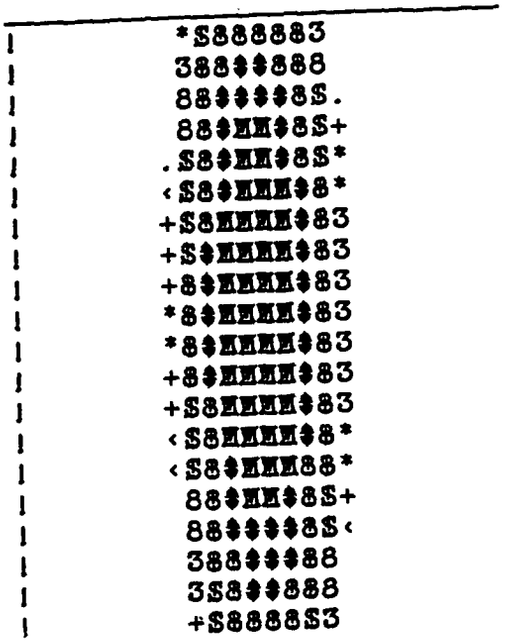
SET 15A



SET 15B



SET 15C



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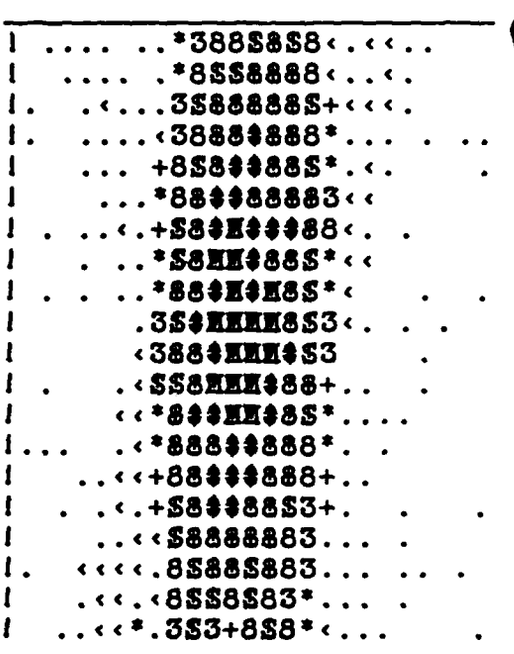
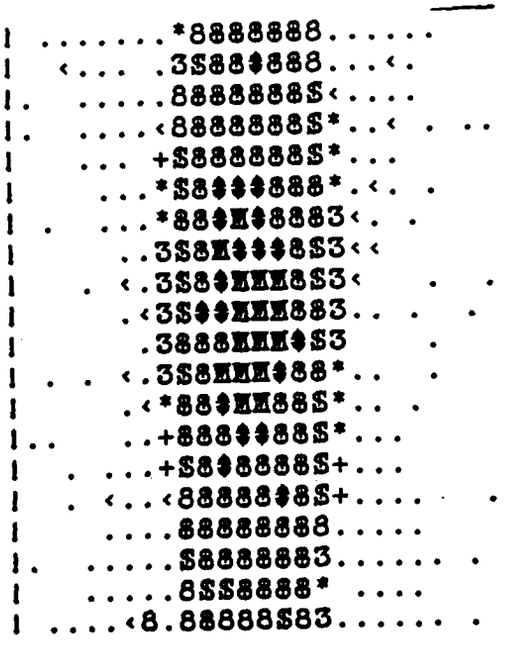
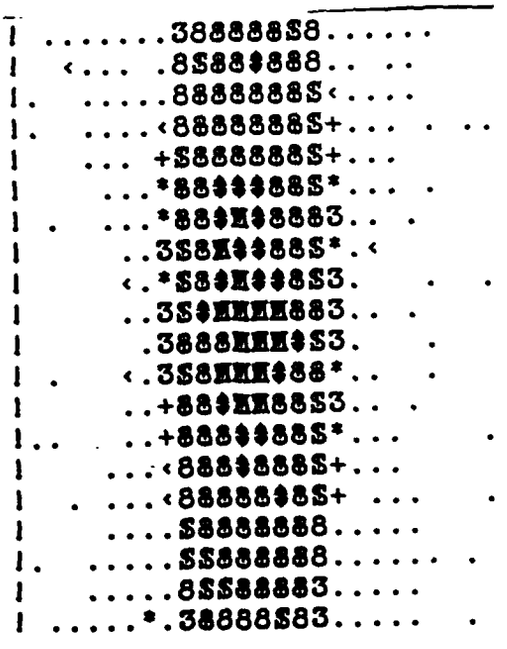


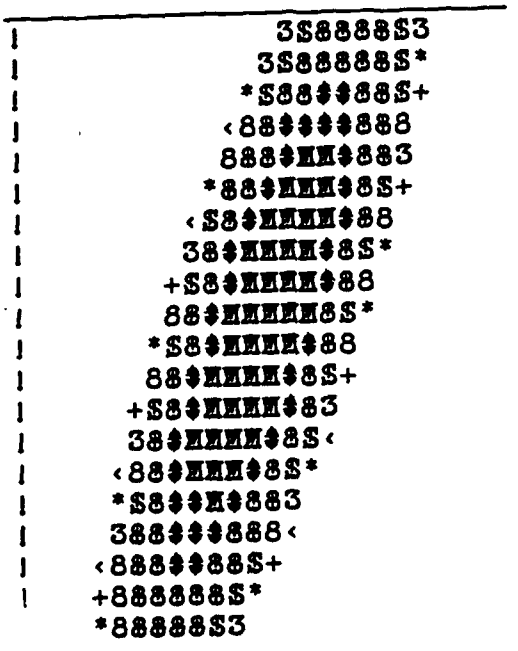
SET 16A



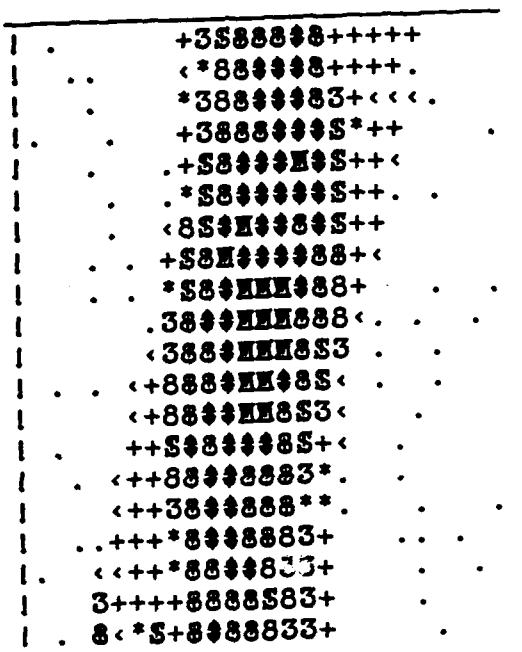
SET 16B



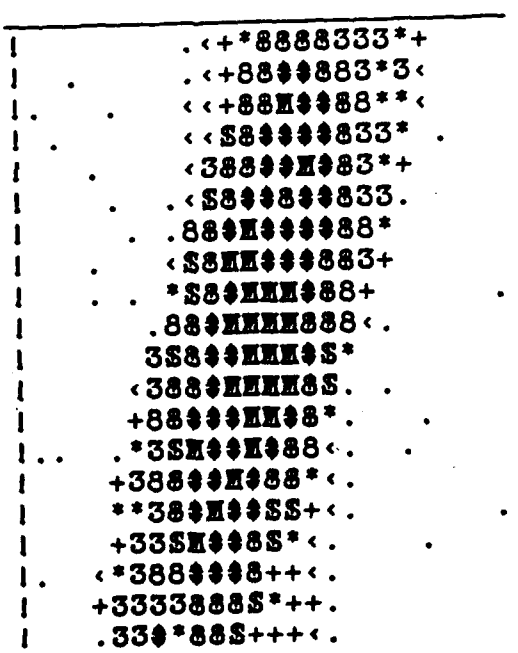
SET 16C



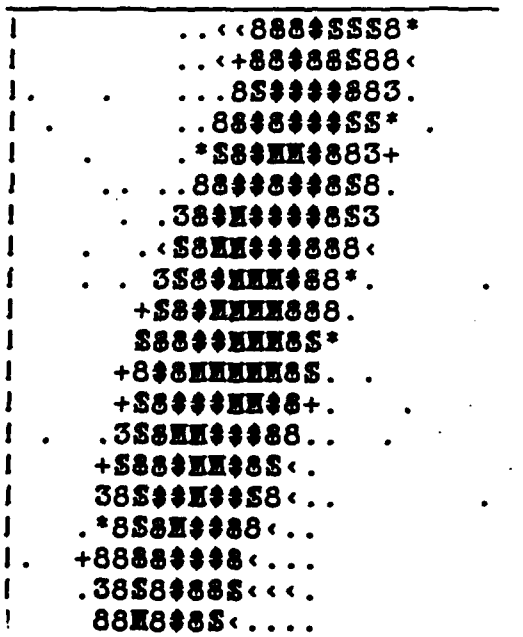
CLEAN



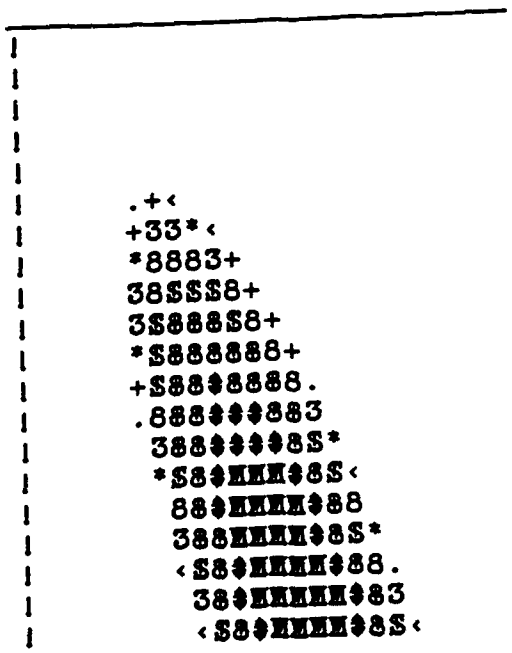
SET 17A



SET 17B



SET 17C



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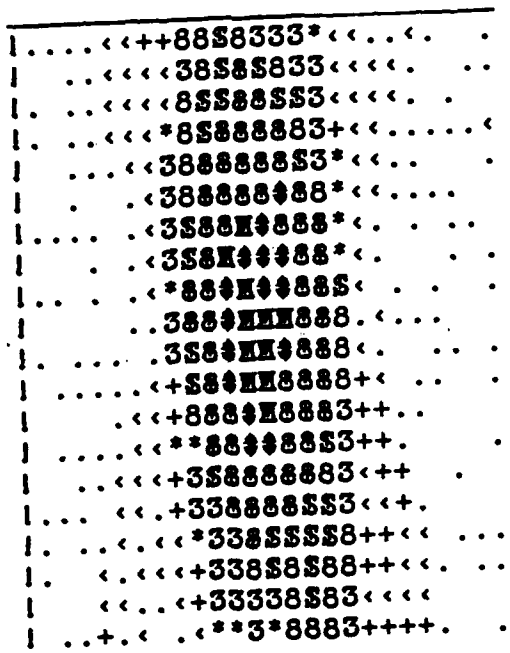
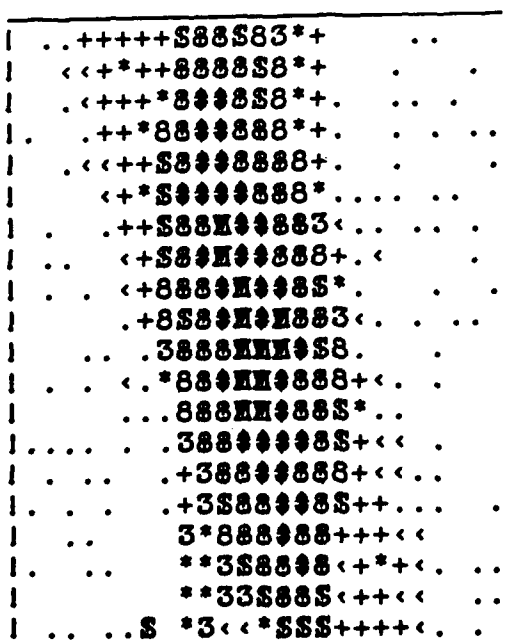
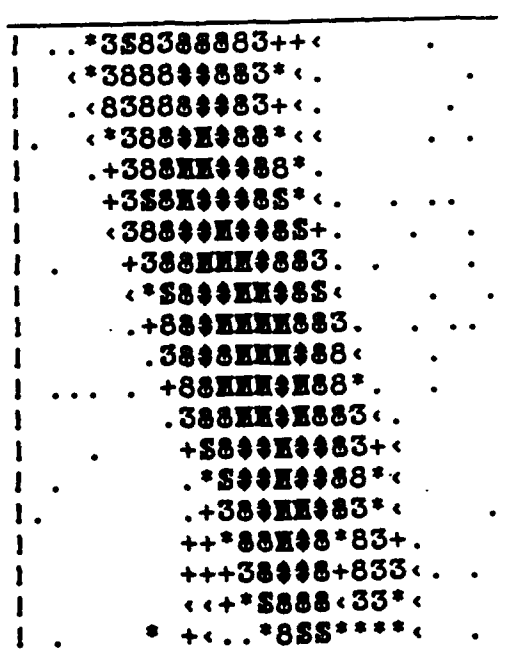


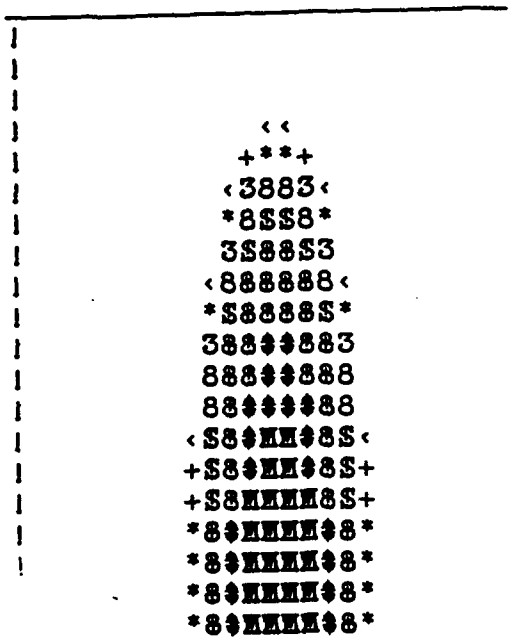
SET 18A



SET 18B



SET 18C



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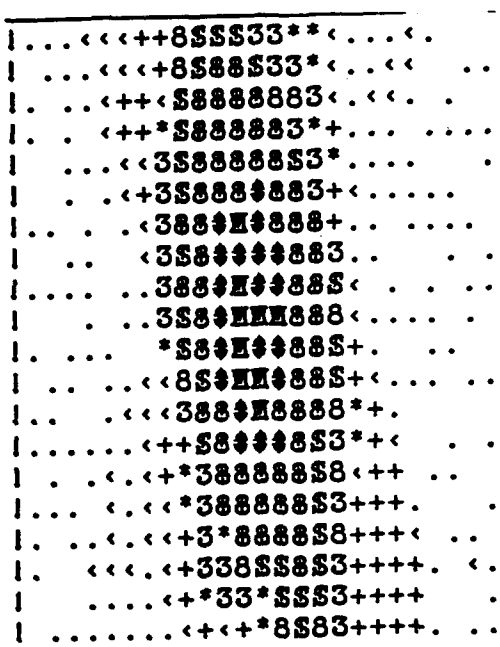

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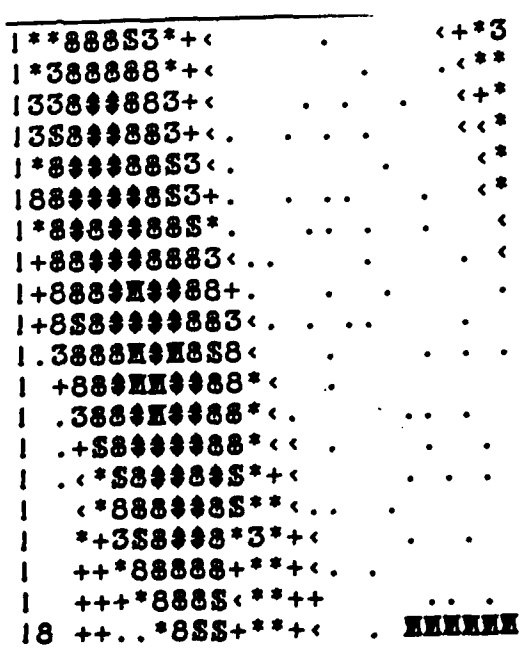
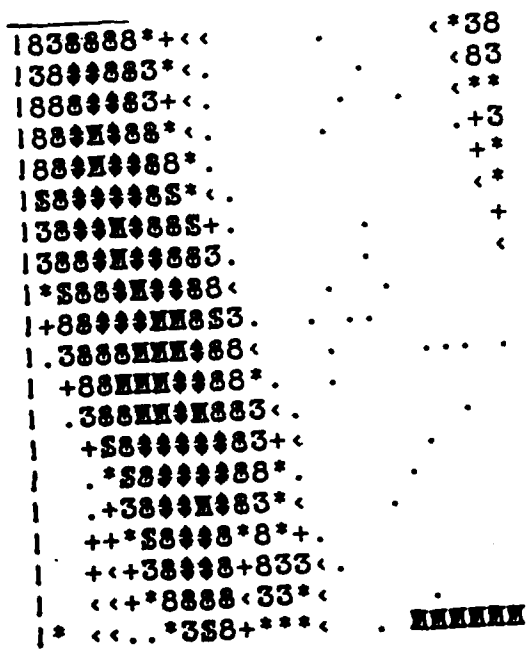
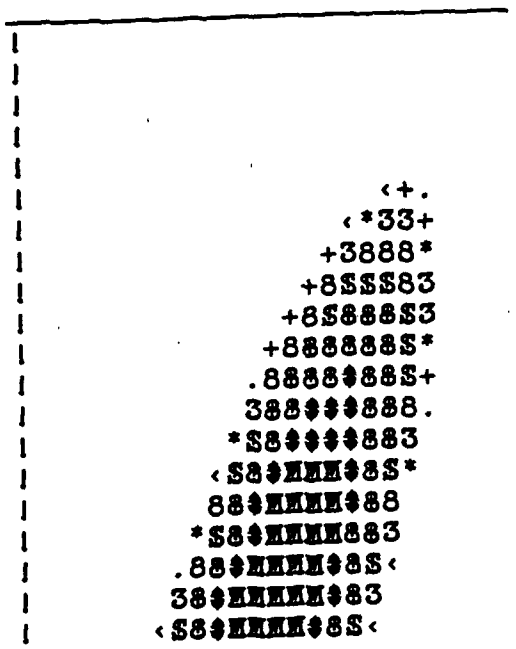


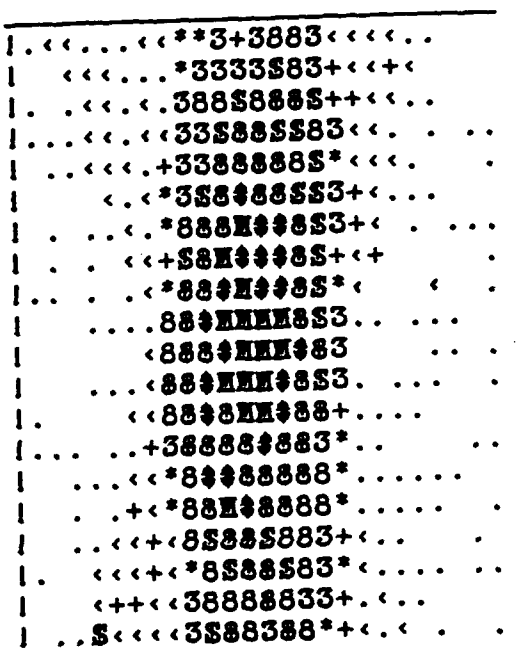
SET 19B



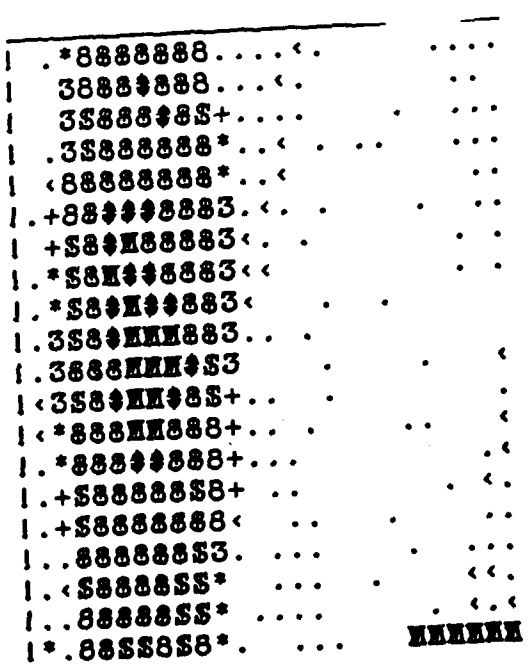
SET 19C



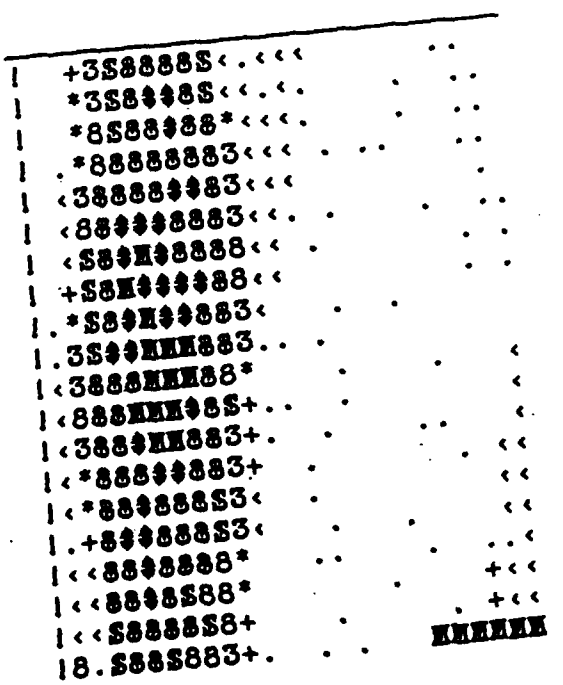
CLEAN



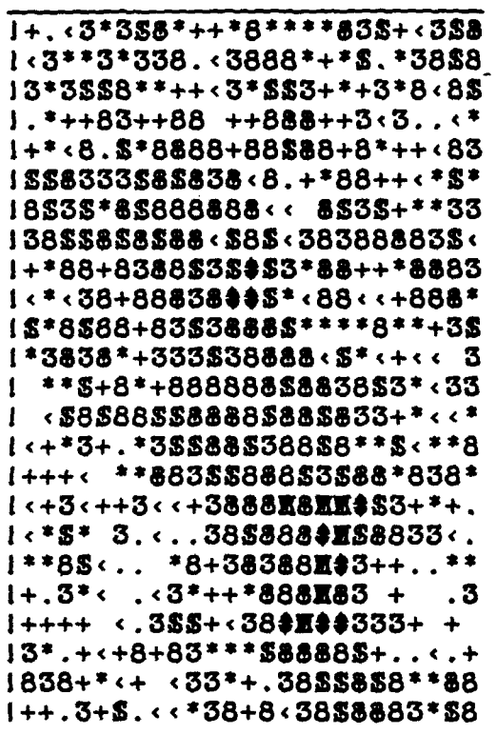
SET 20A



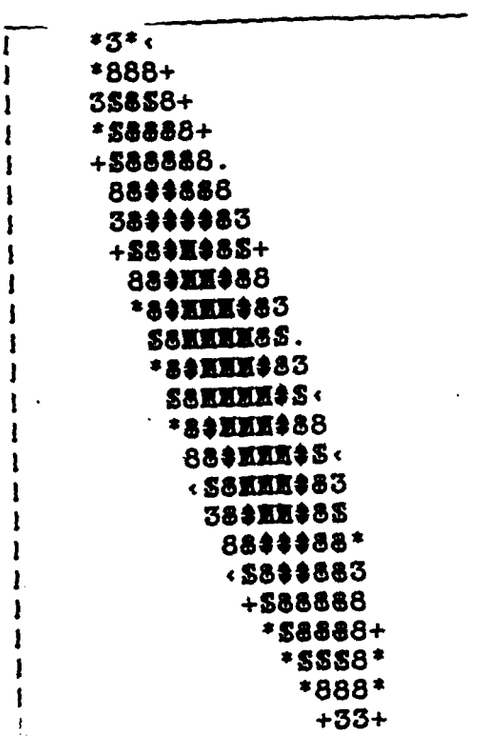
SET 20B



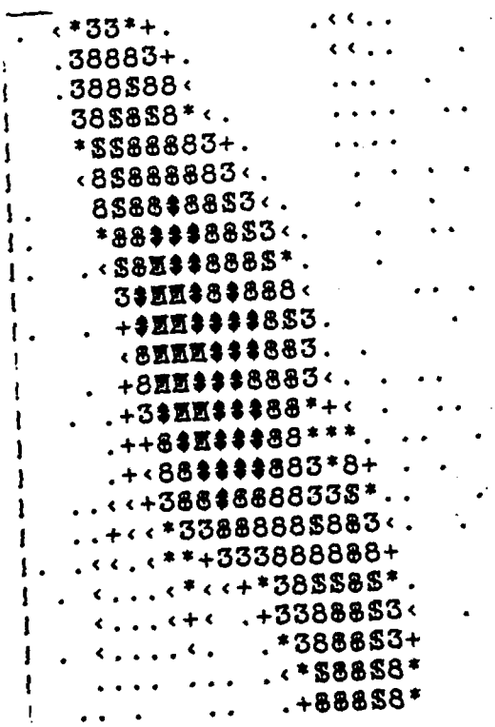
SET 20C



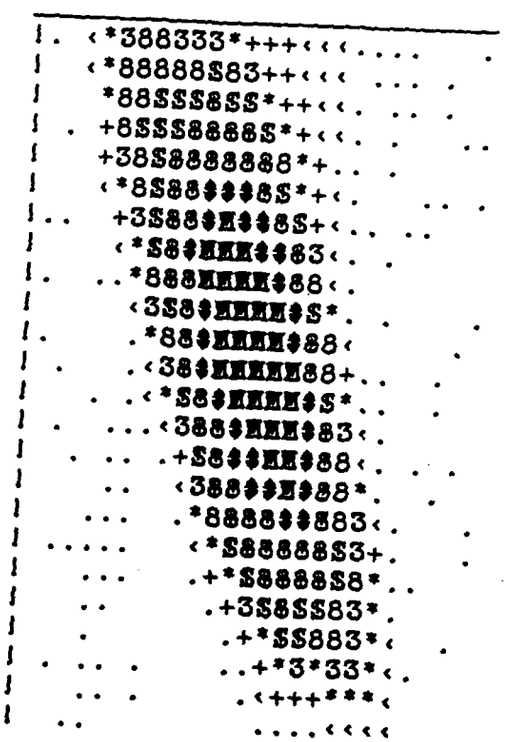
NOISY



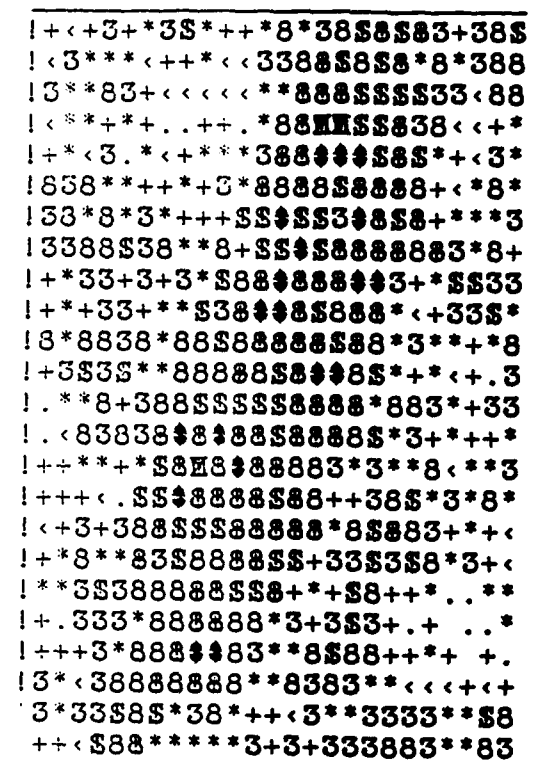
NOISE-FREE



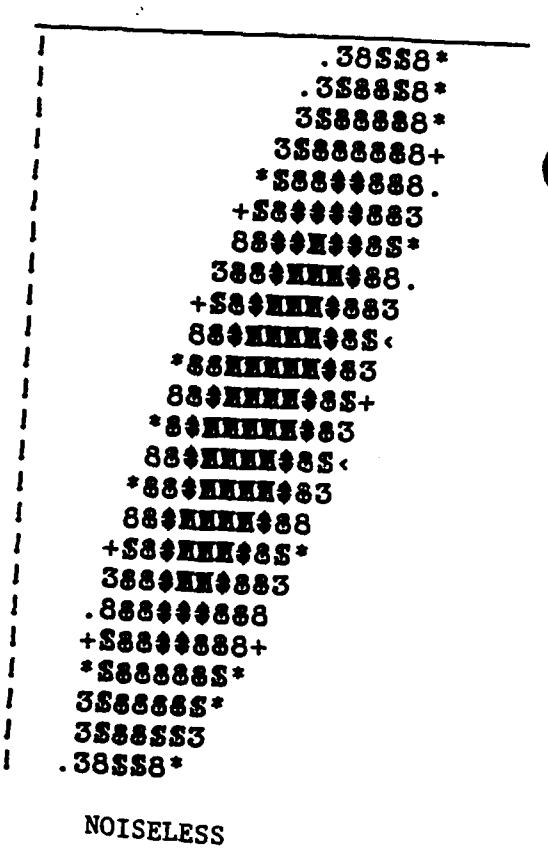
PROPAGATION



RECURSION



NOISY



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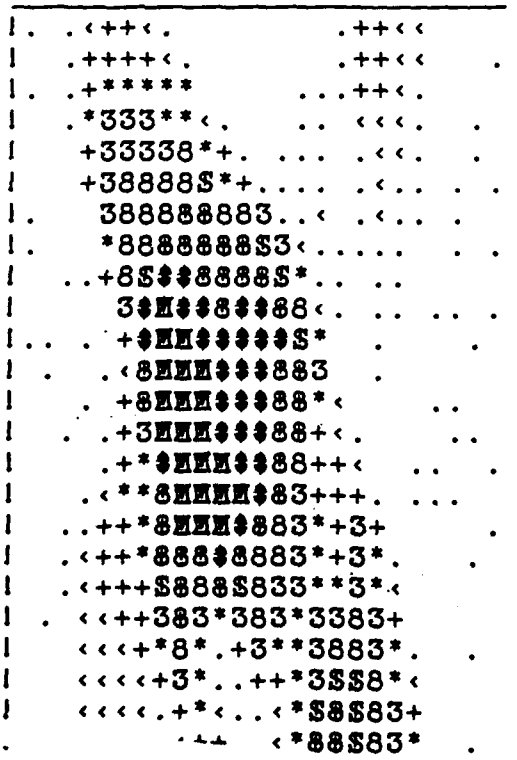
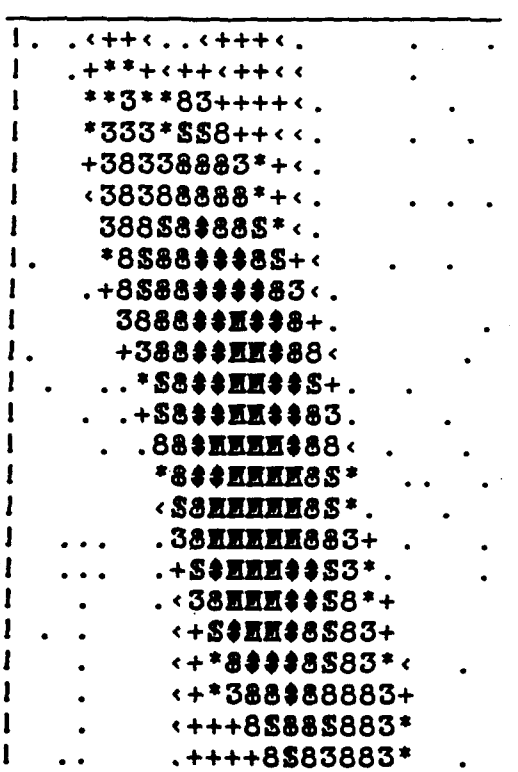
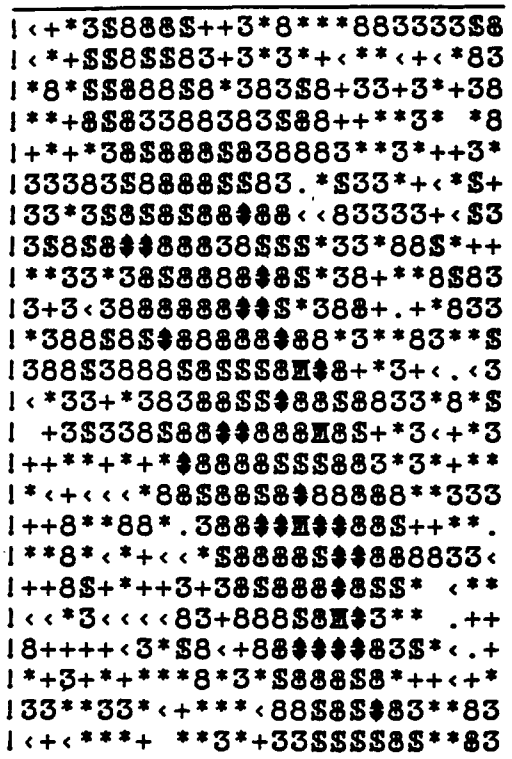


PROPAGATED

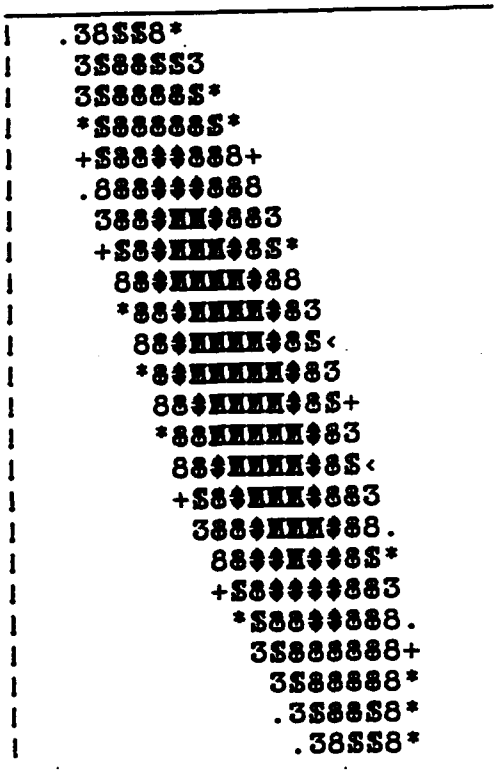


RECURSION

SET 3 - 600 NODES
TRAINING



NOISY



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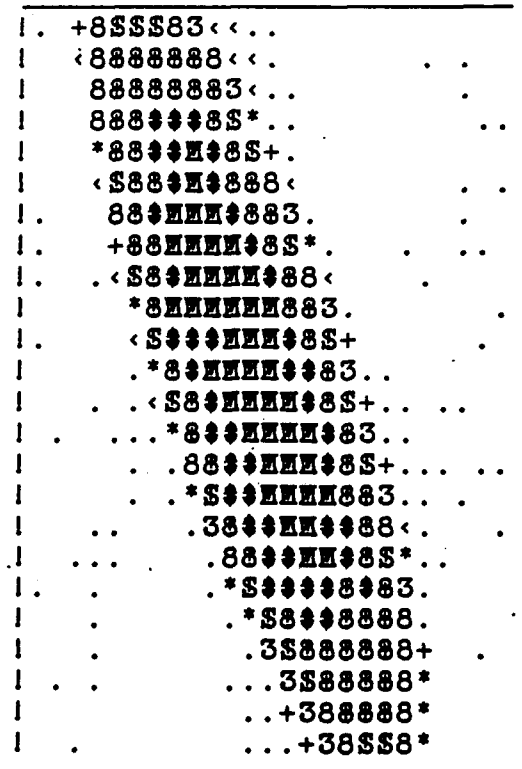
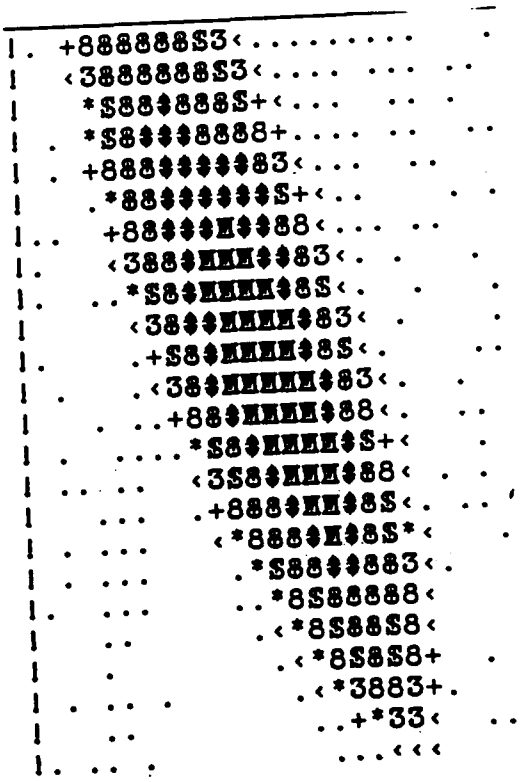
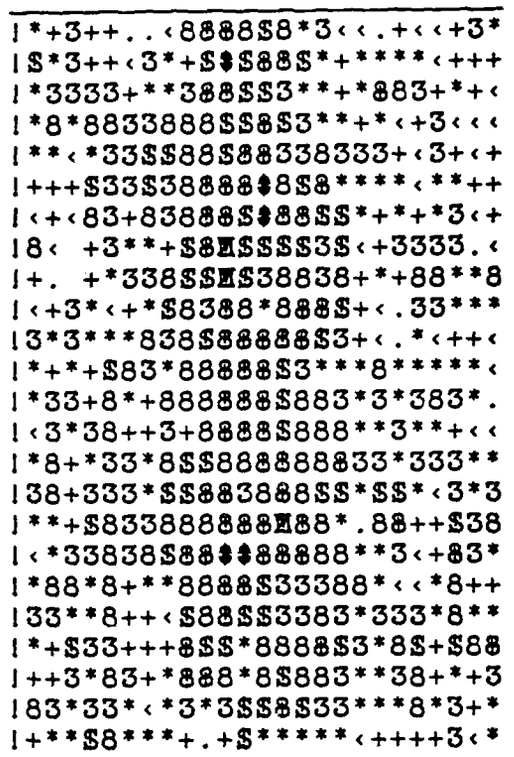


PROPAGATION

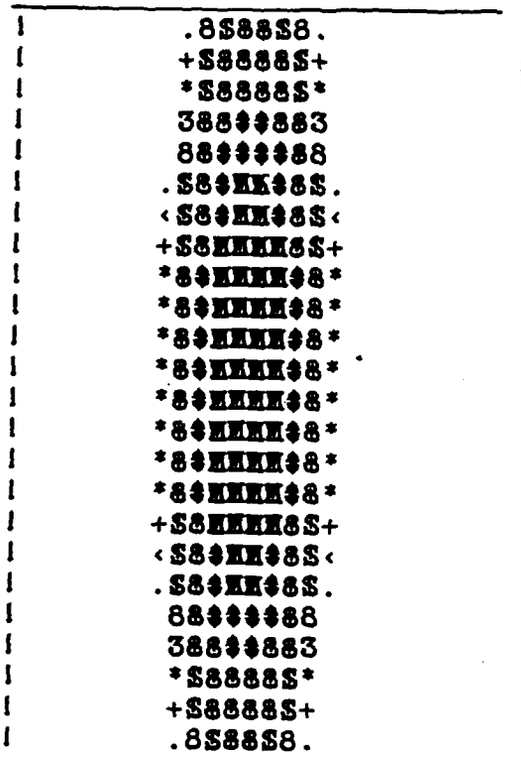


RECURSION

SET 5 - 600 NODES
TRAINING



NOISY



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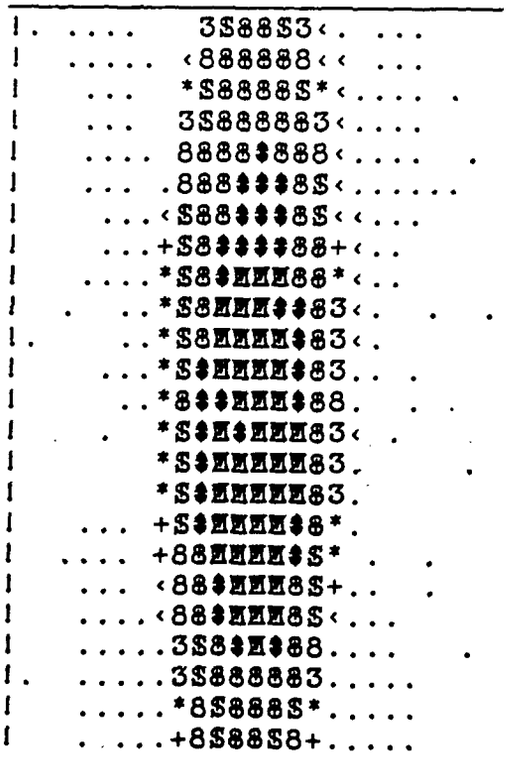
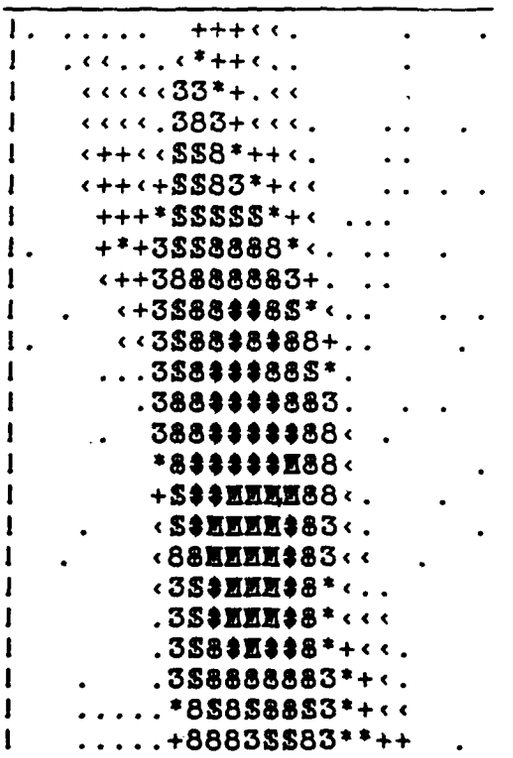
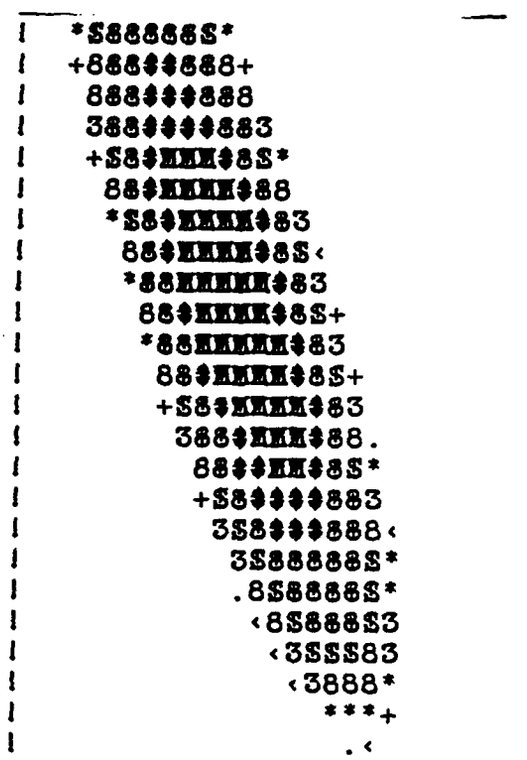


PROPAGATED



RECURSION

NOISY



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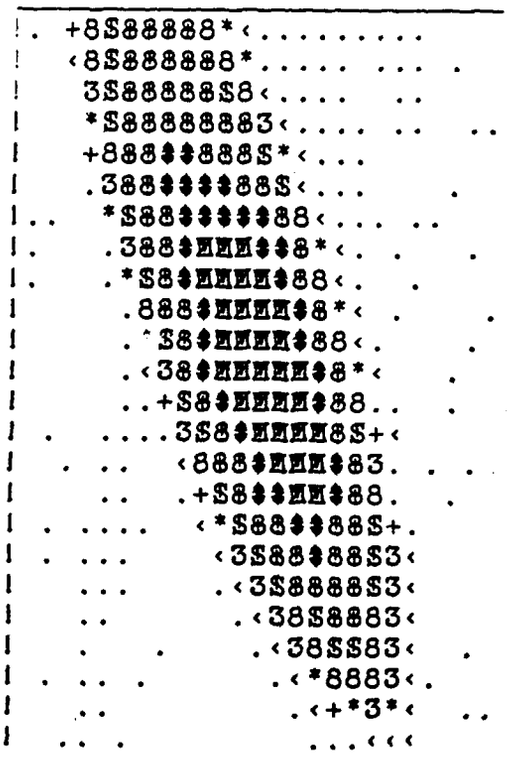
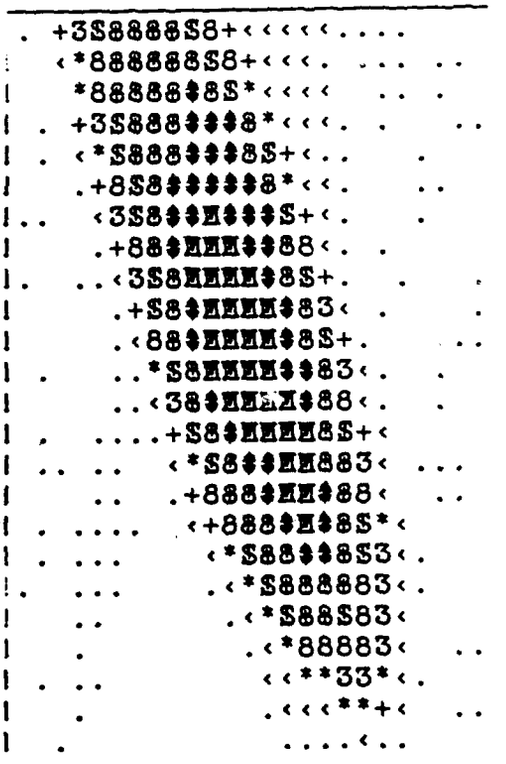
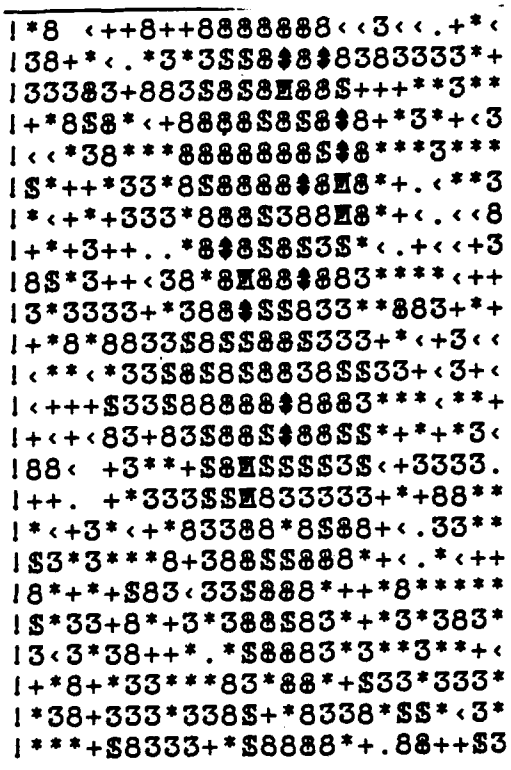


PROPAGATED



RECURSION



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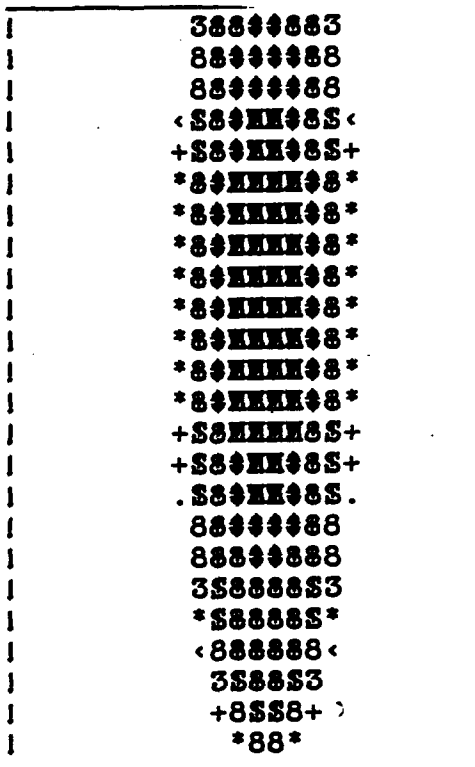

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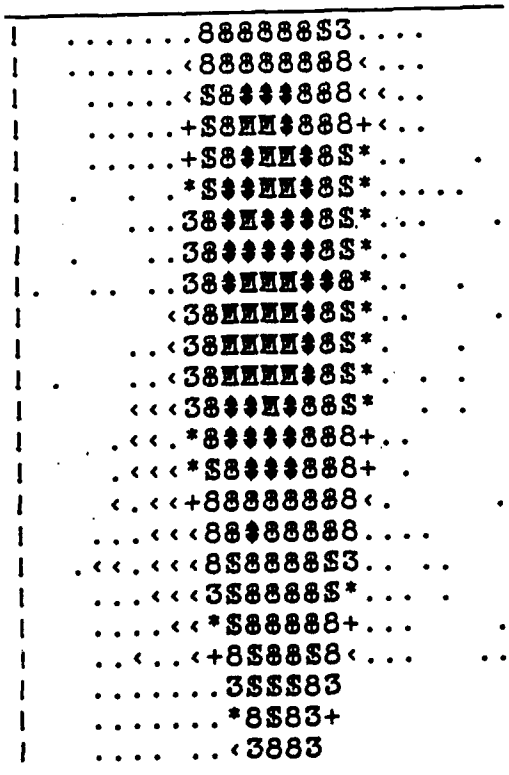
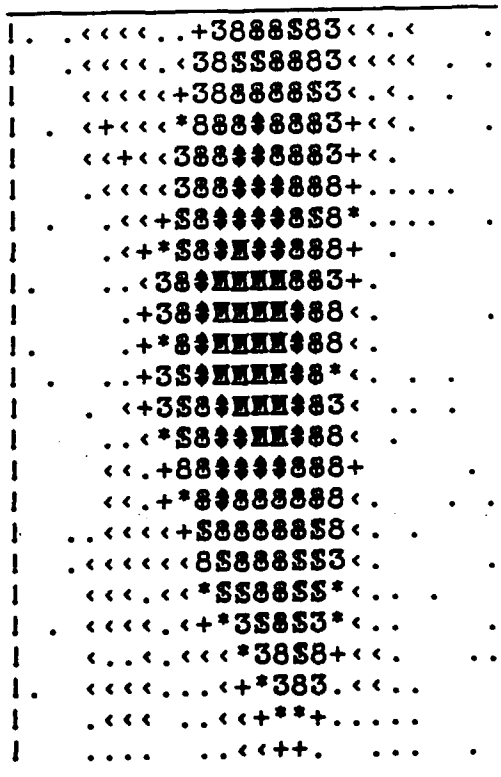
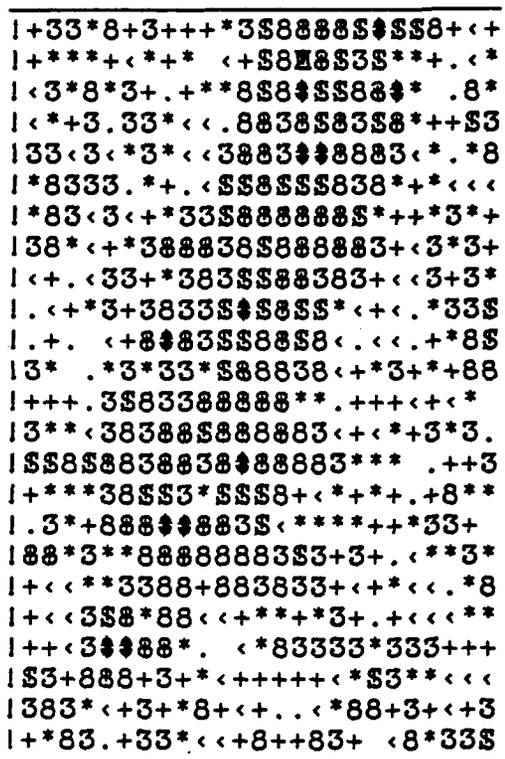


PROPAGATED

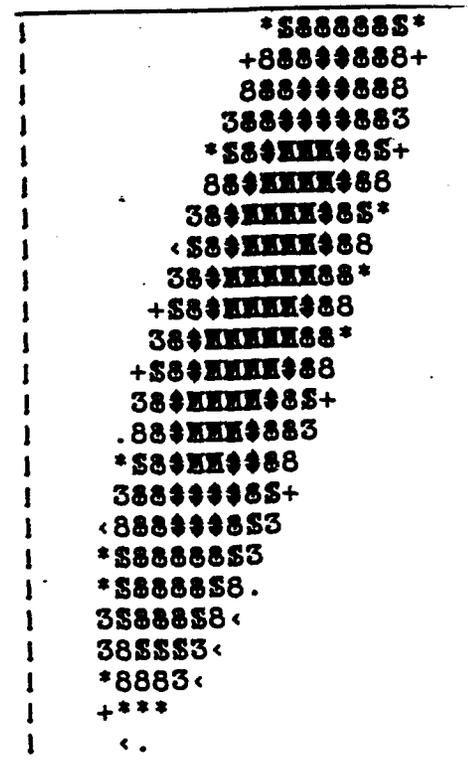


RECURSION

SET 8 - 600 - Nodes
TRAINING



NOISY



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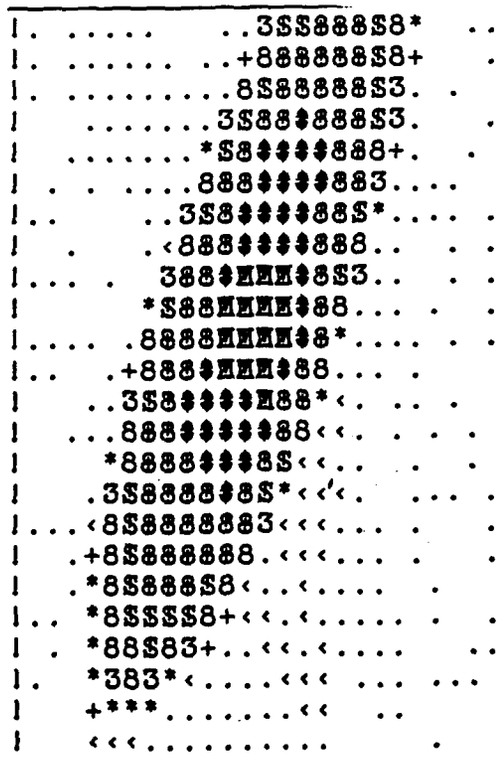
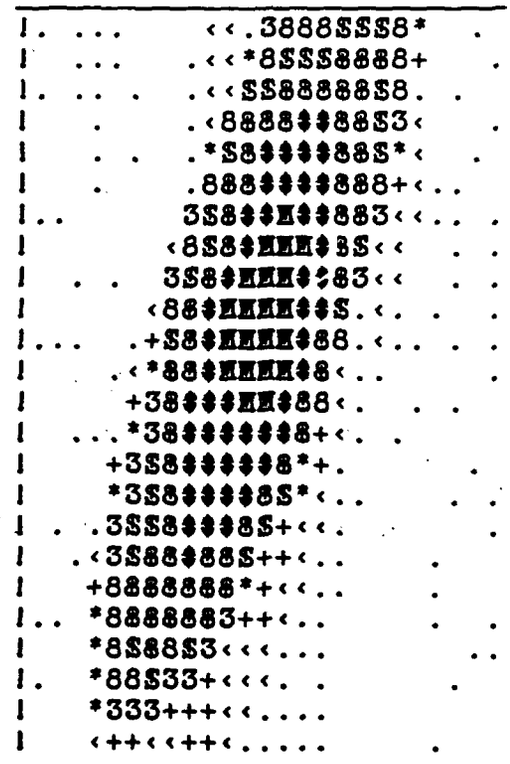
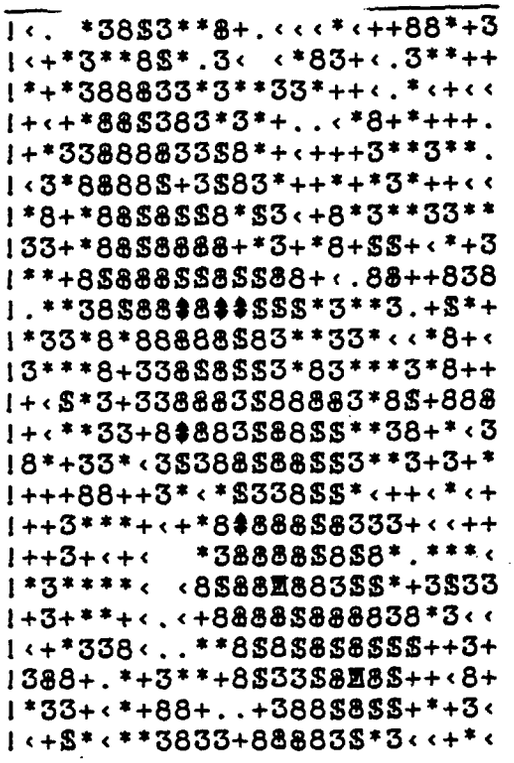


PROPAGATED



RECURSION



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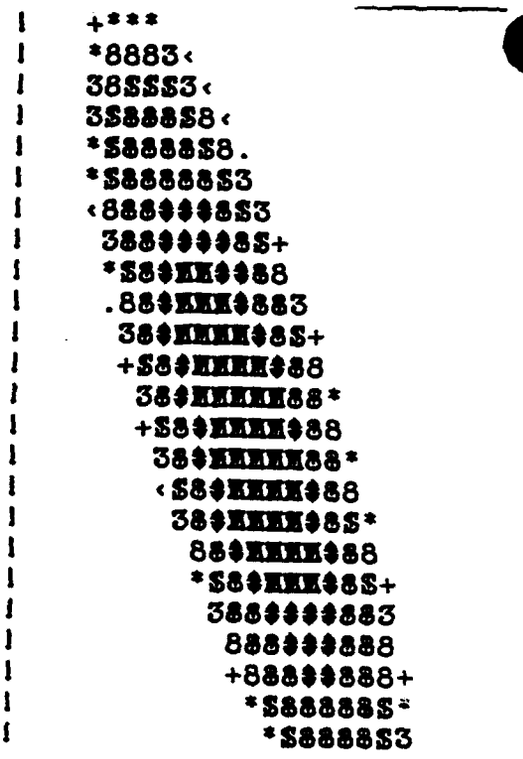

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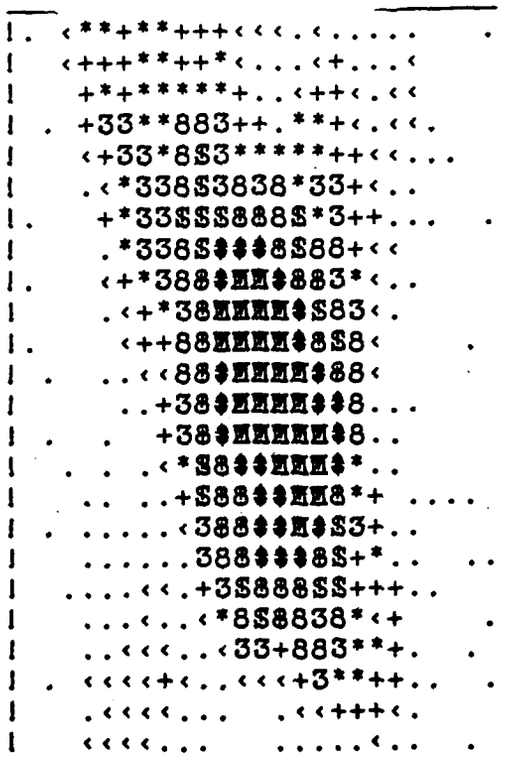

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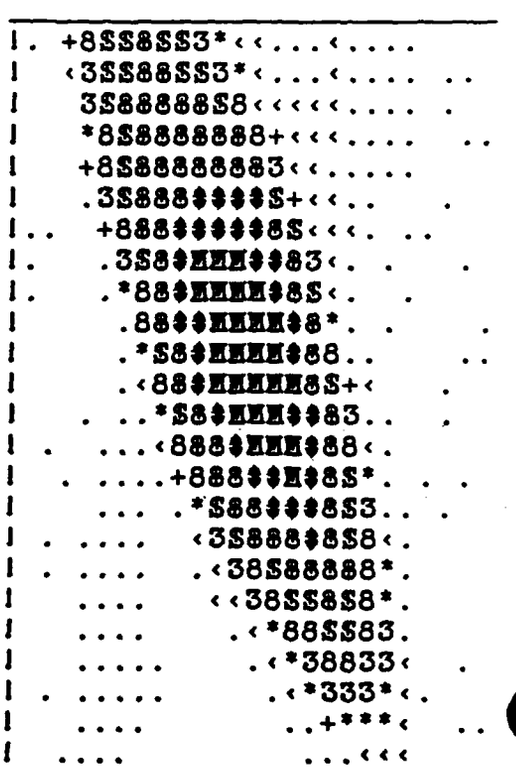

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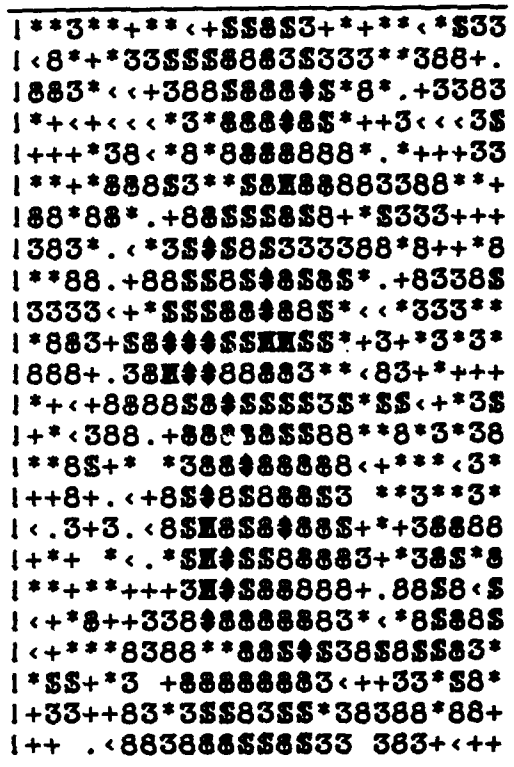

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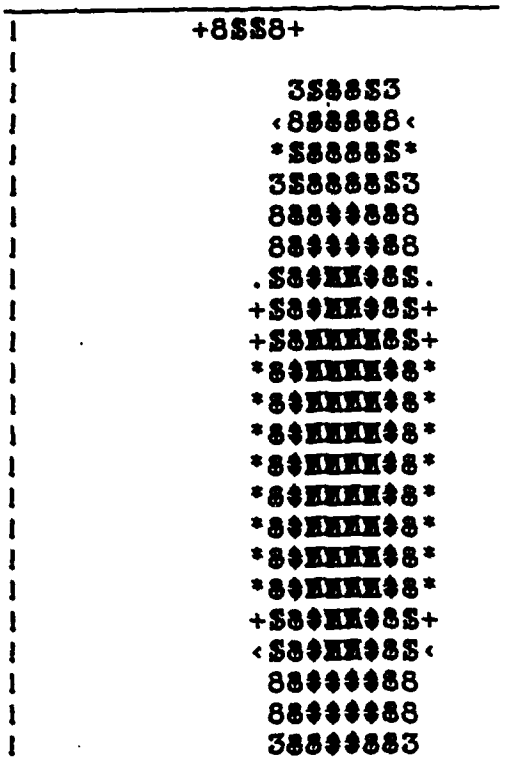

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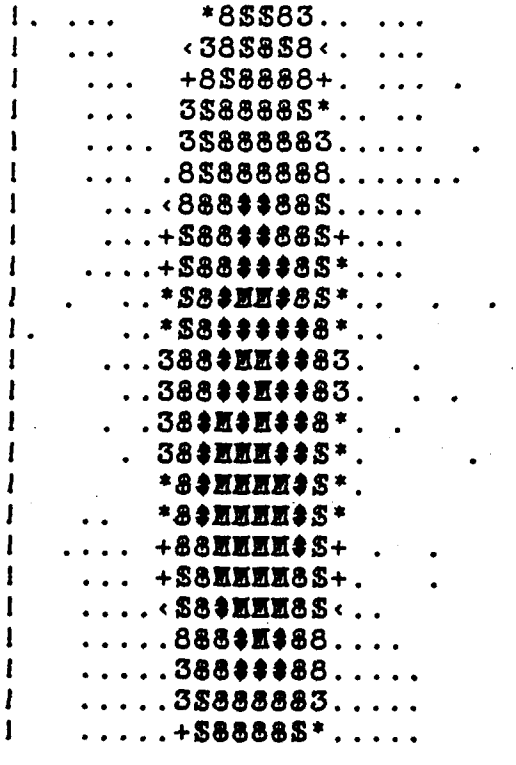

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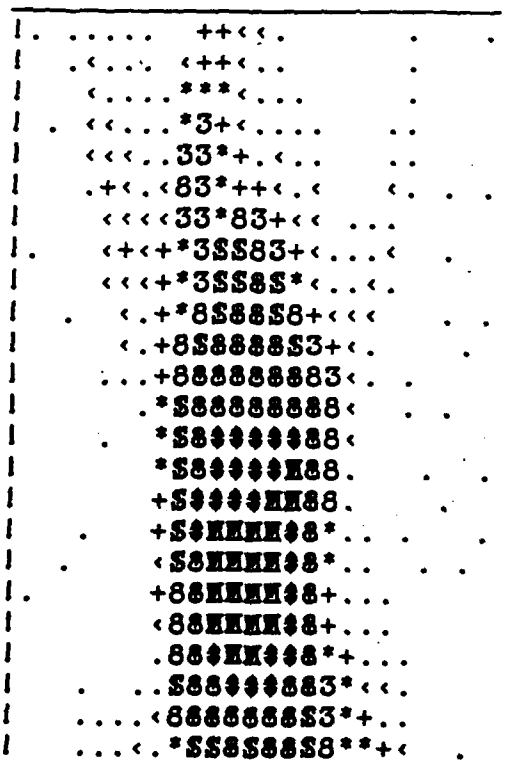

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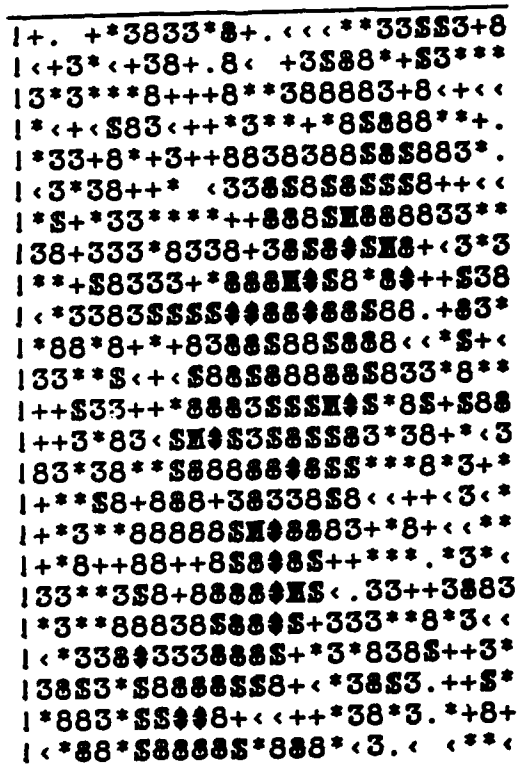

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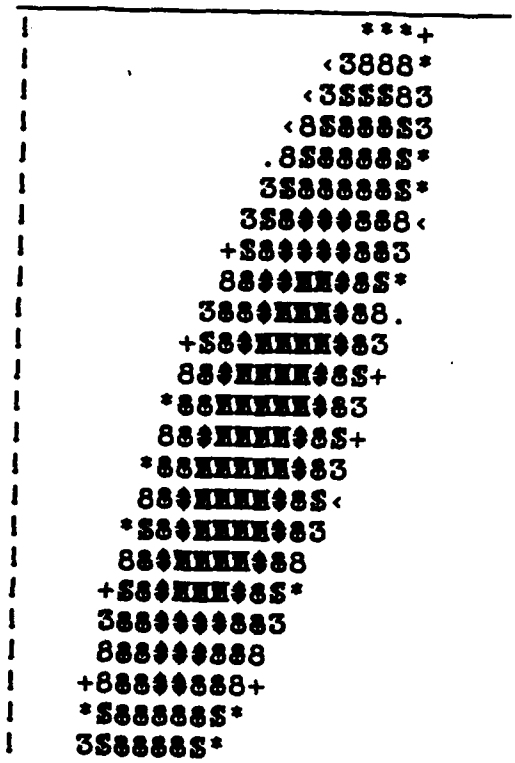

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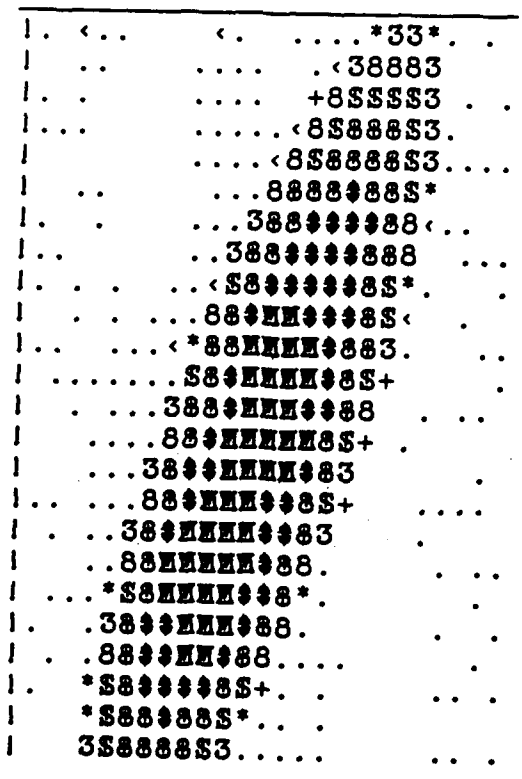

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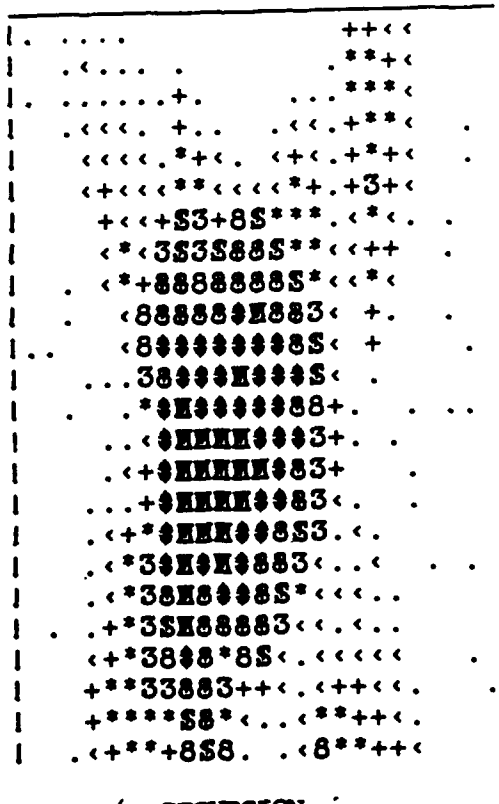

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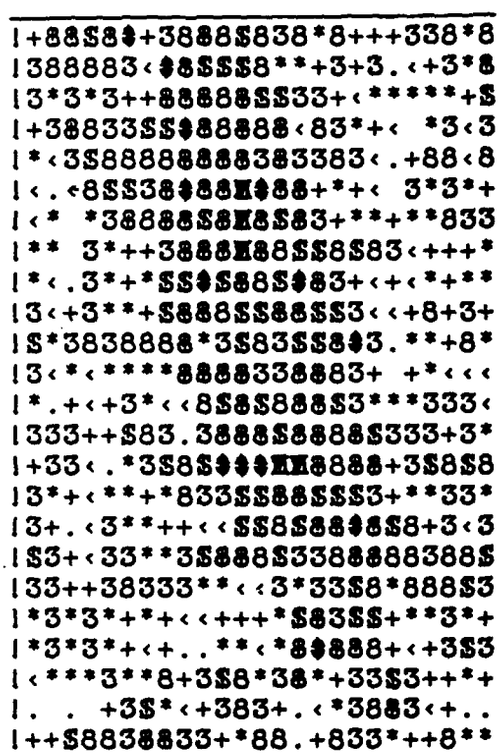

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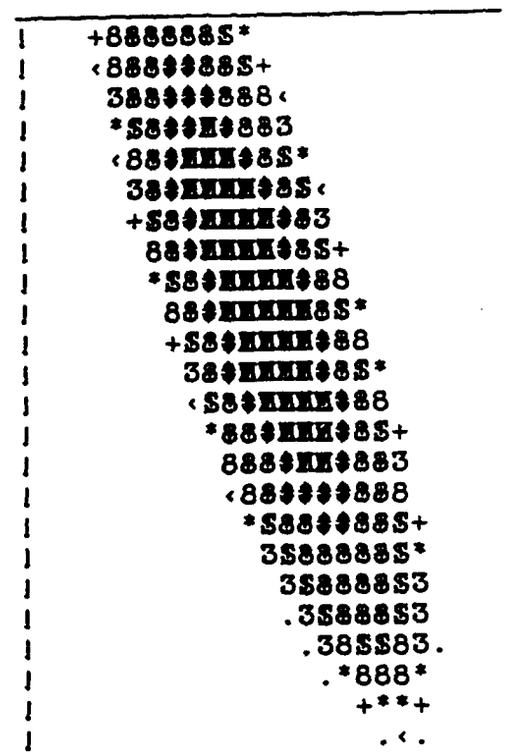

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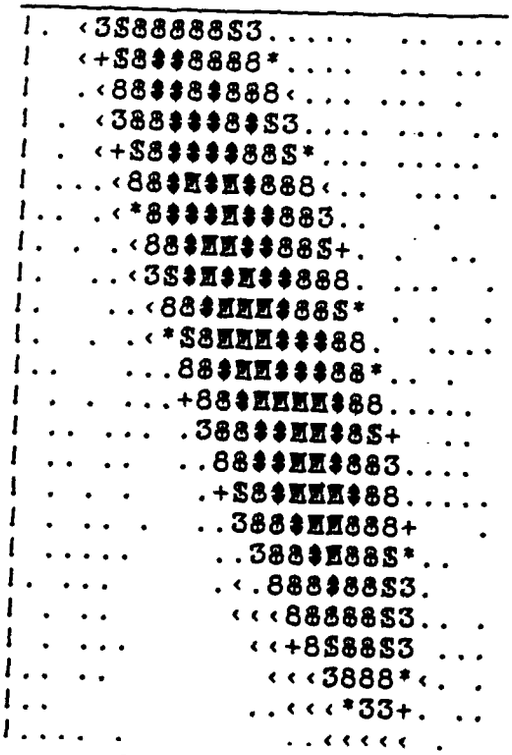

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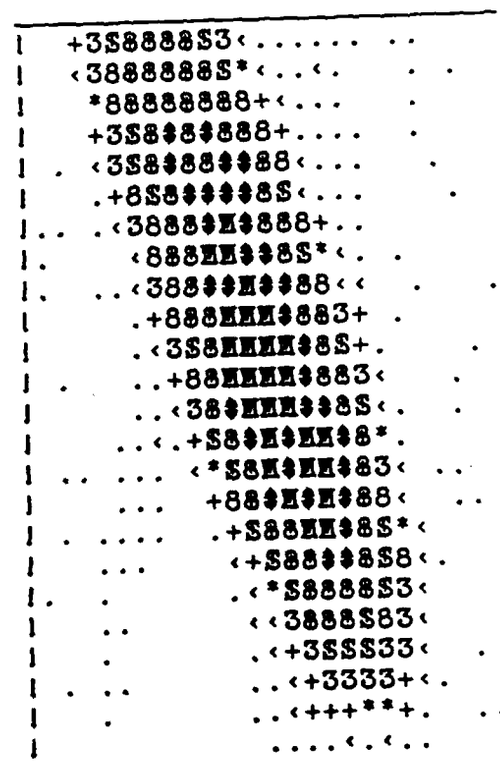

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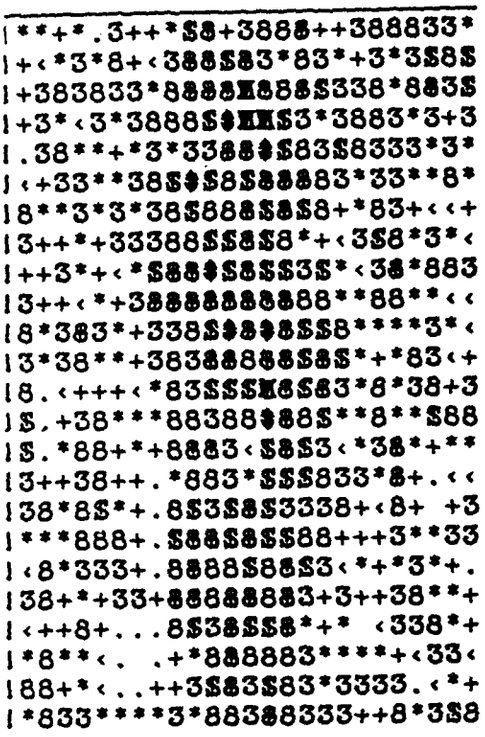

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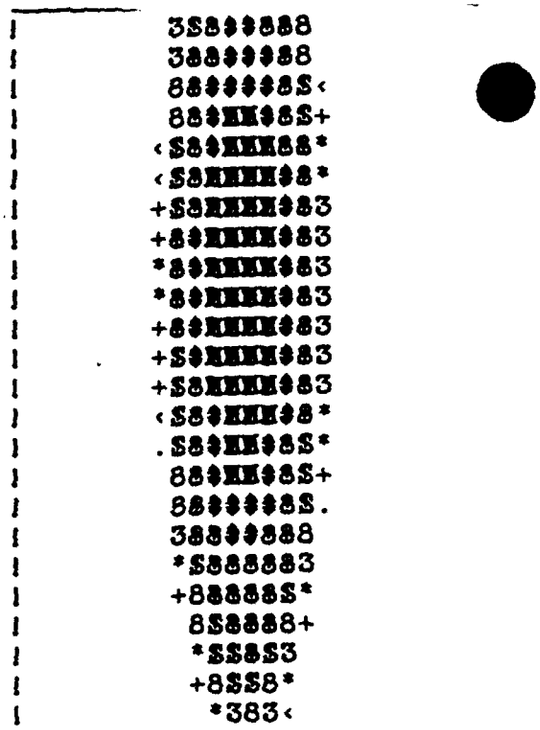

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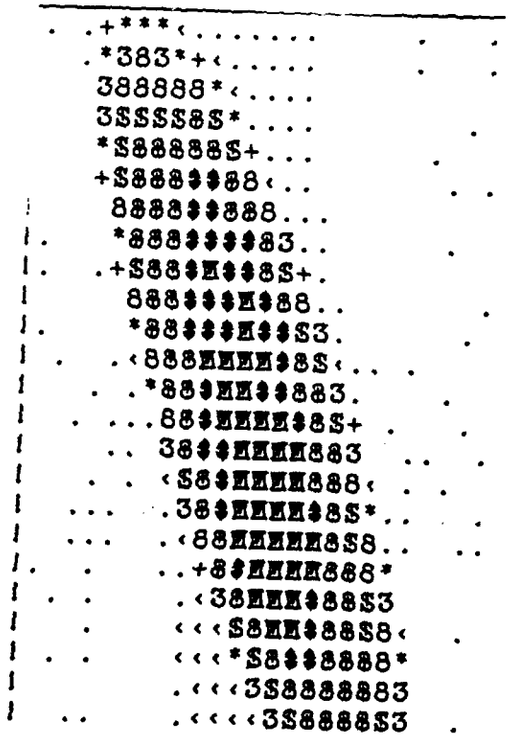

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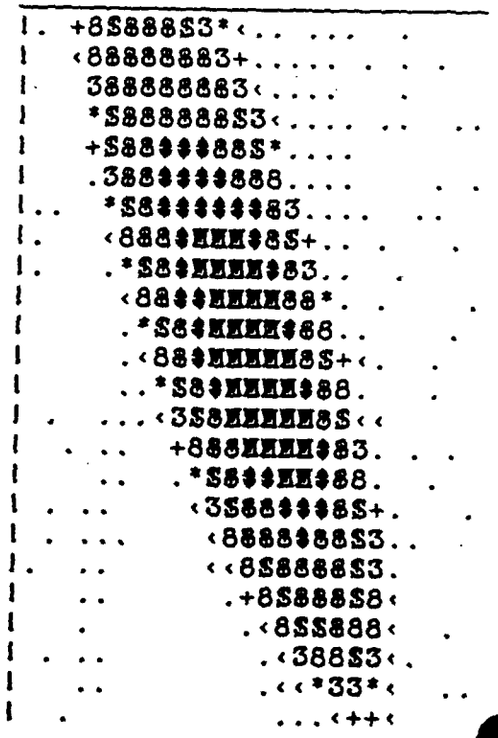

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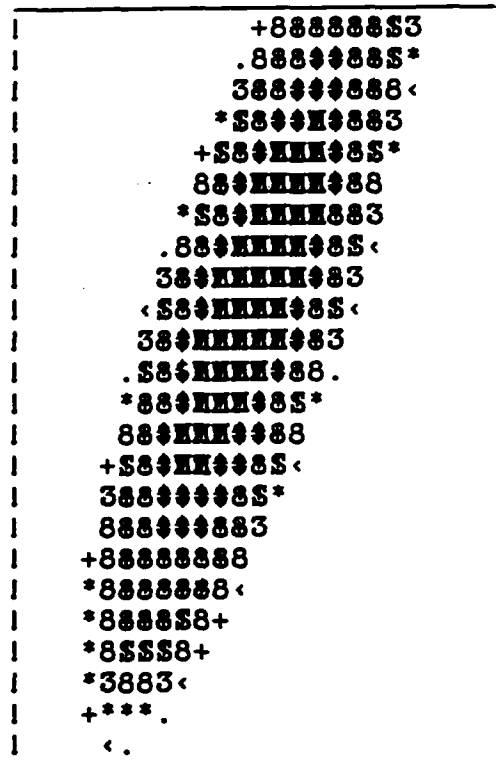

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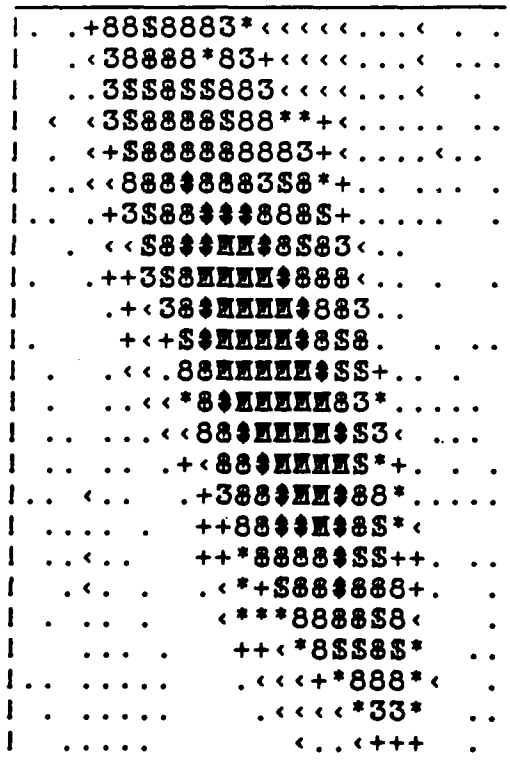

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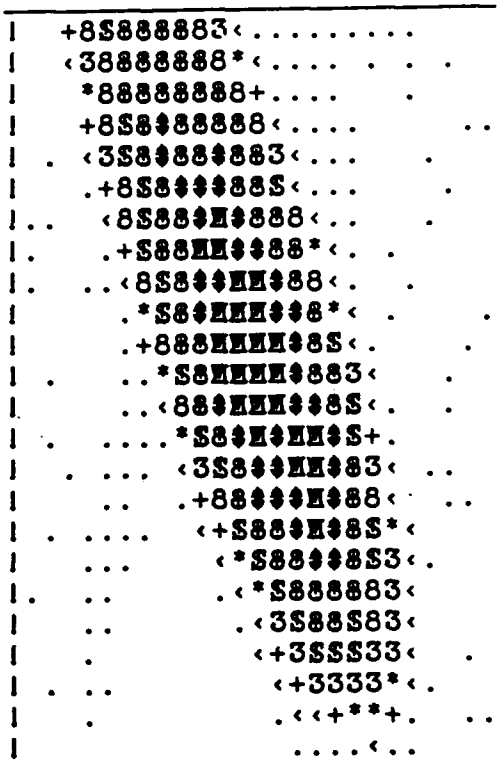

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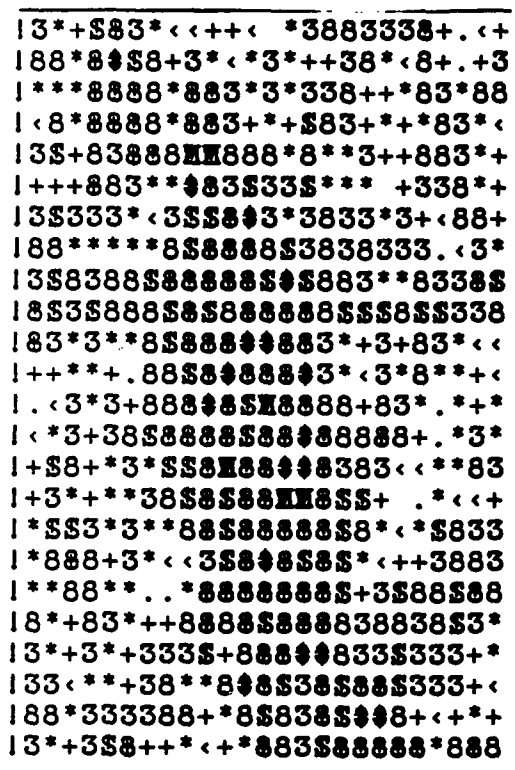

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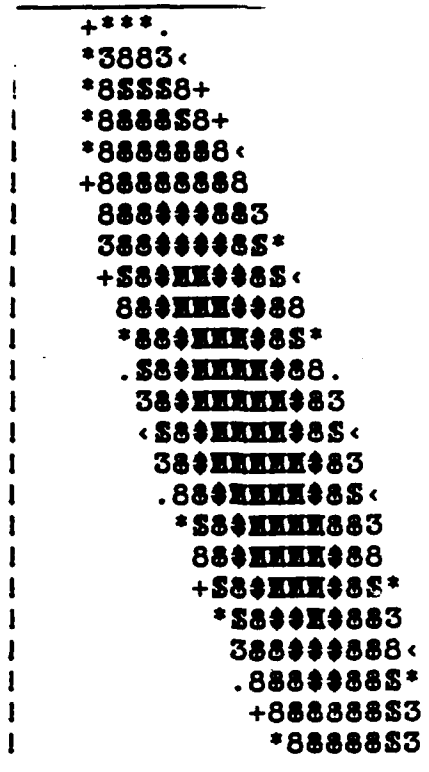

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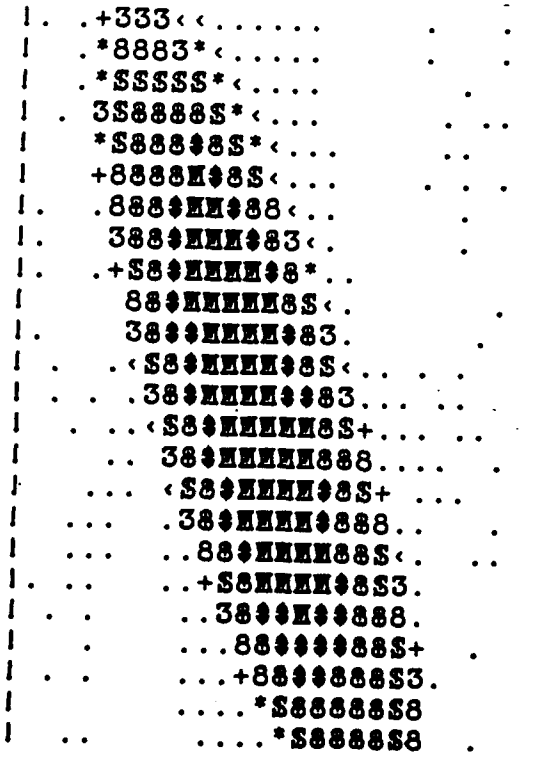

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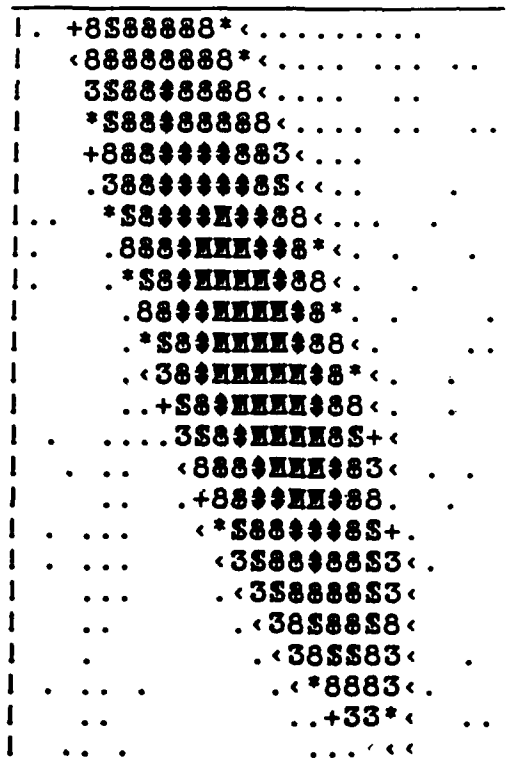

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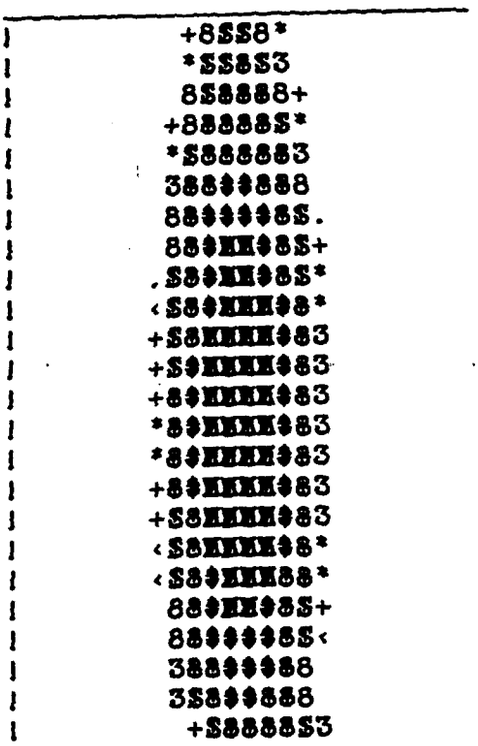

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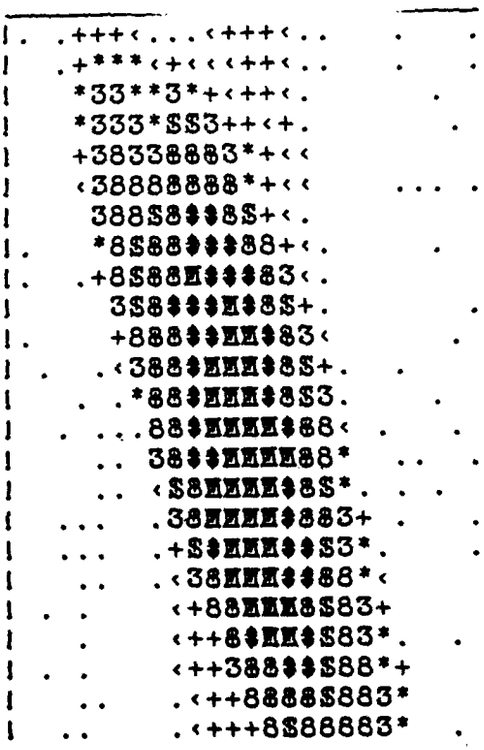

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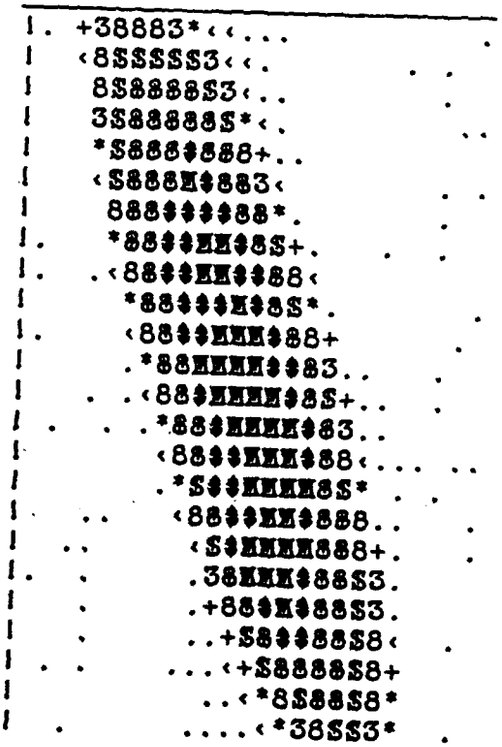

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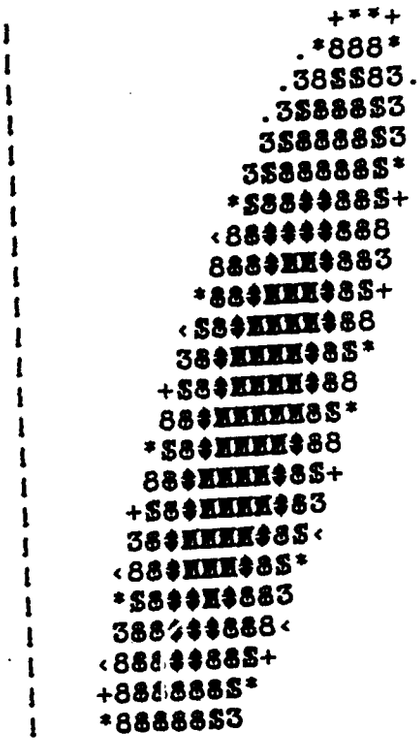

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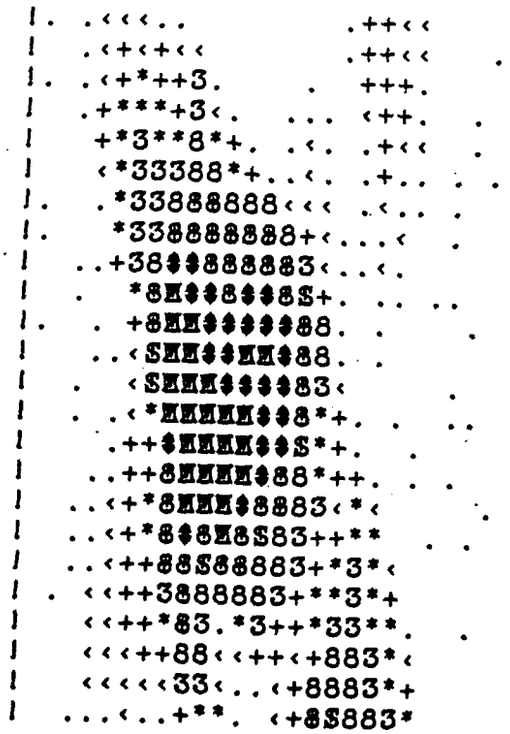

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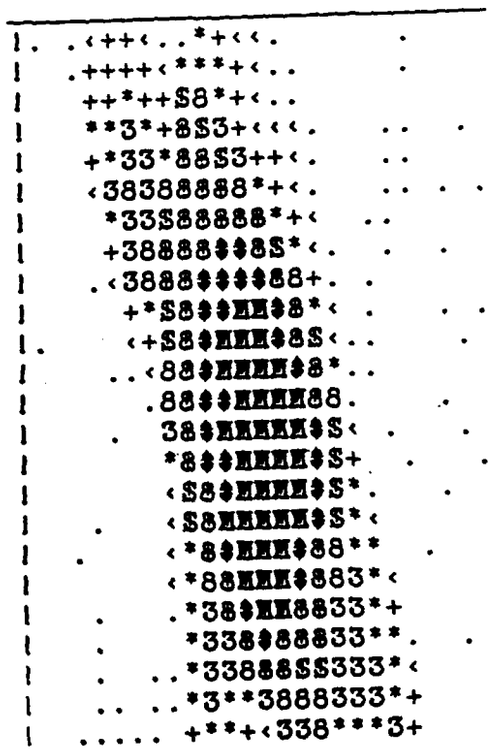

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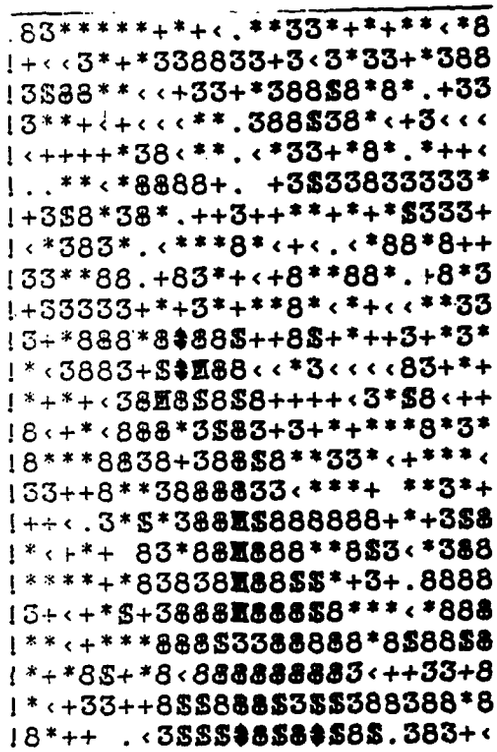

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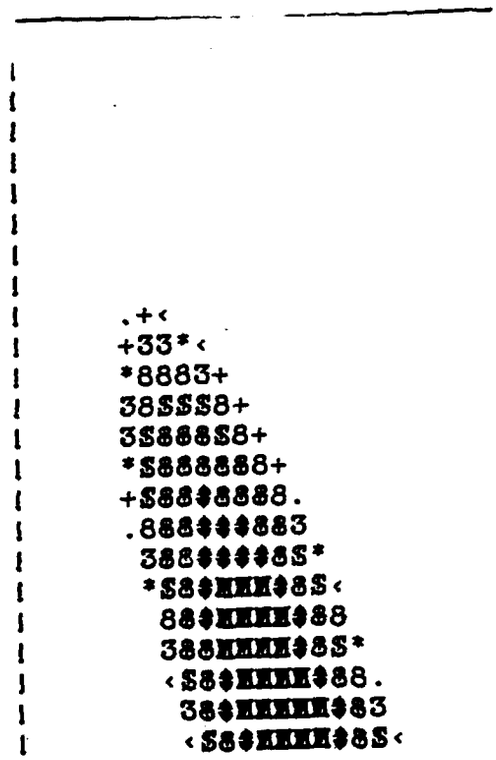

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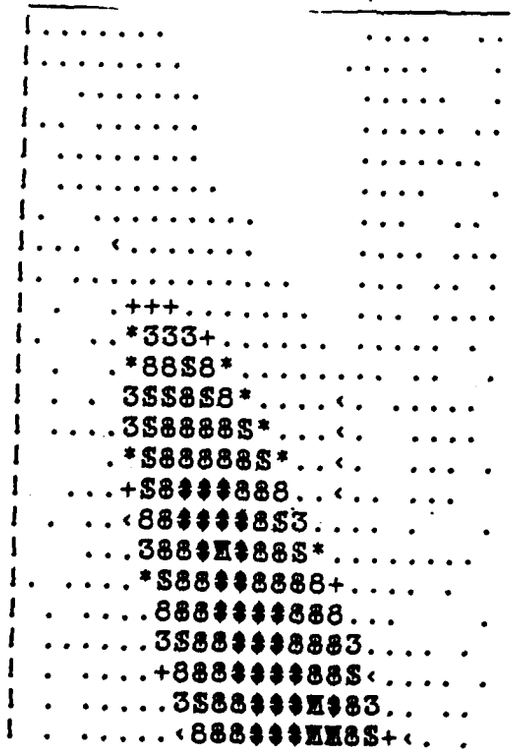

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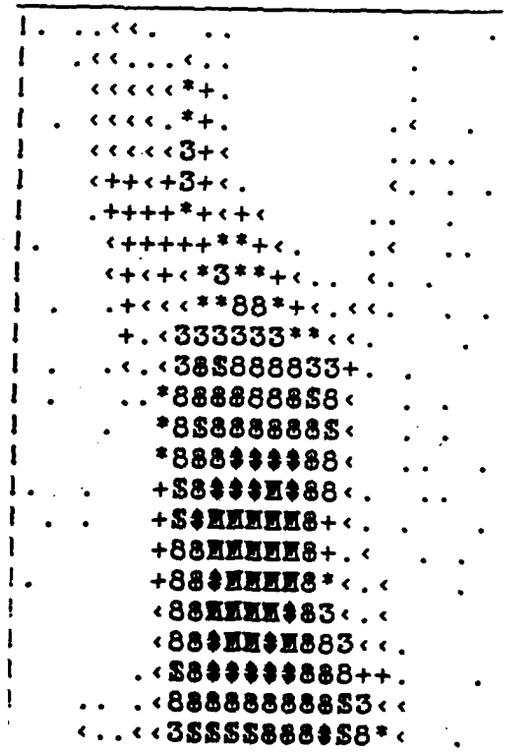

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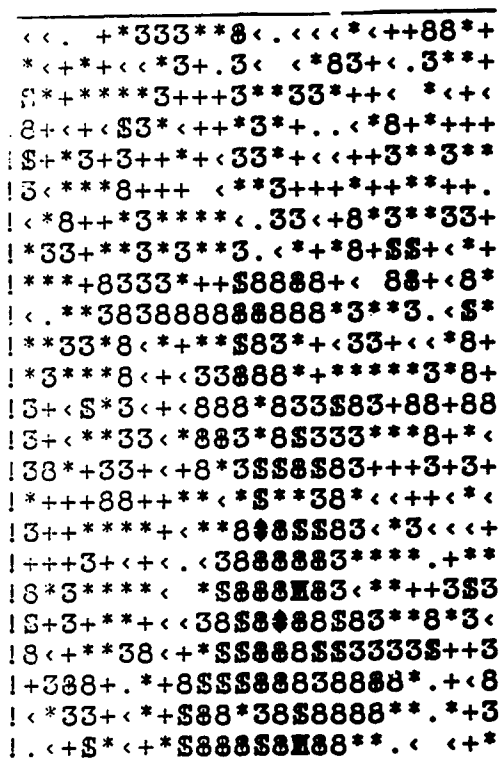

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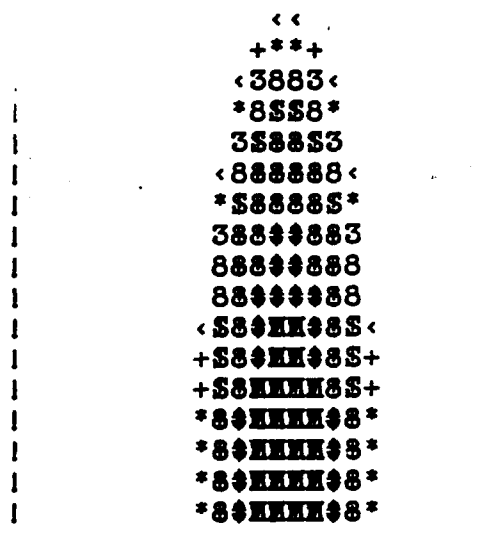

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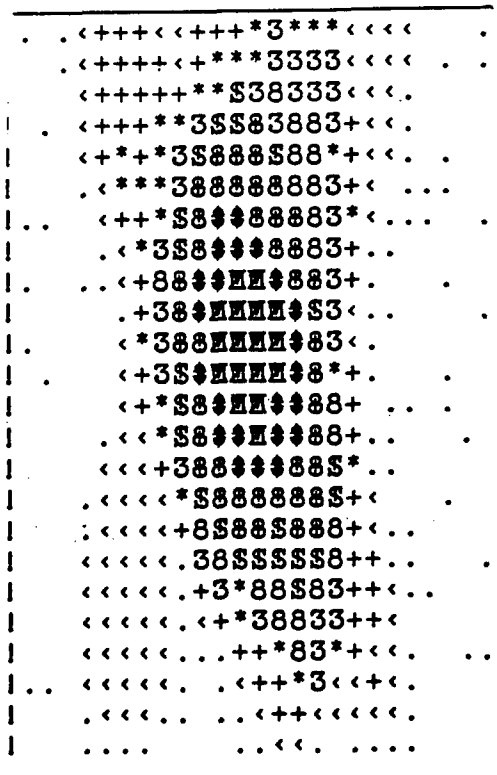

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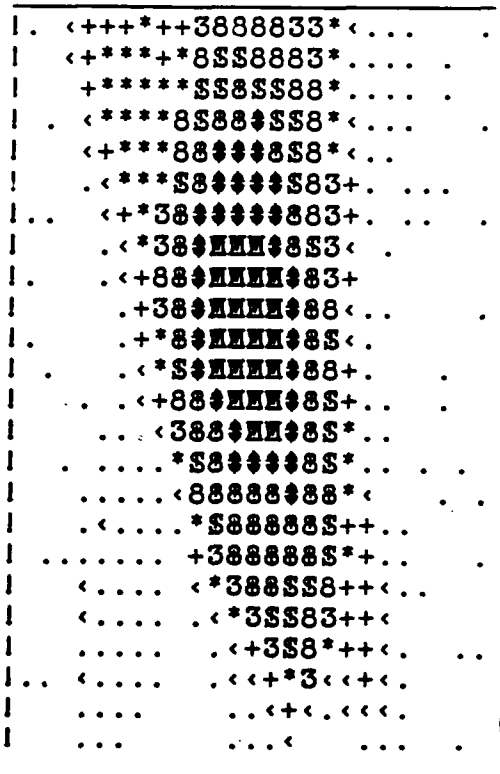

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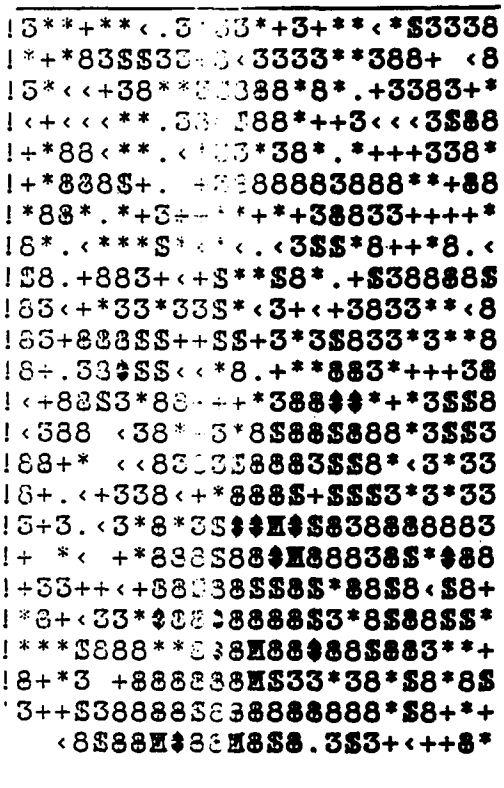

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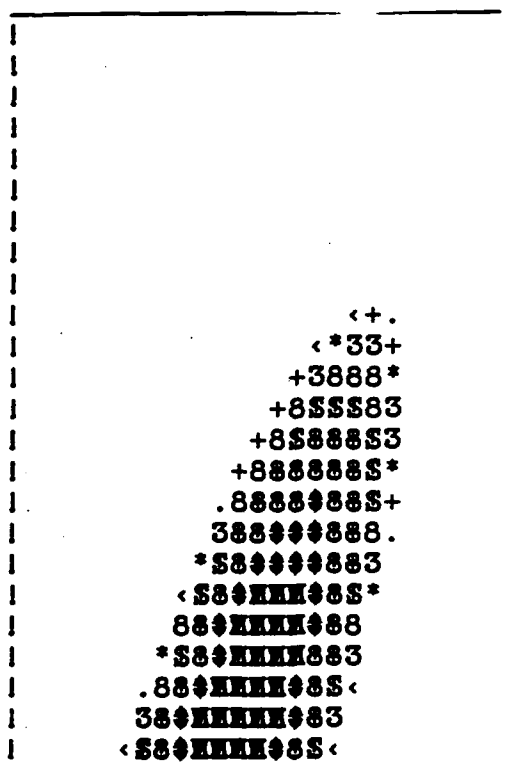

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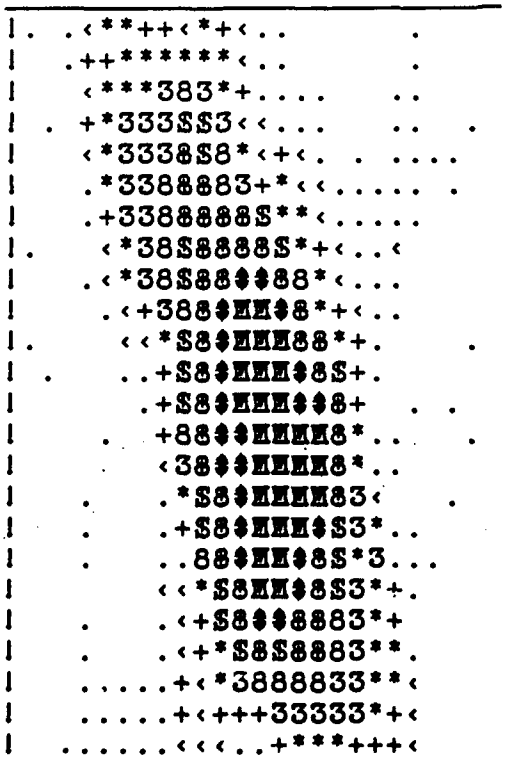

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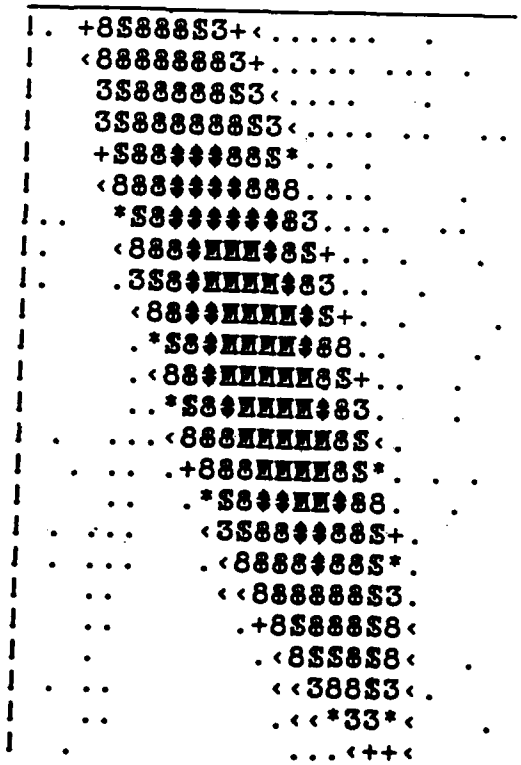

RECURSION

Appendix D: References

Eberhart, Russell C. and Dobbins, Roy W., Editors. Neural Network PC Tools: A Practical Guide. San Diego, CA: Academic Press Inc., 1990.

Baffes, Paul T. NETS User's Guide (Version 2.0 of NETS). Lyndon B. Johnson Space Center: Software Technology Branch, September 1989.

Maren, Alianna, Harston, Craig, and Pap, Robert. Handbook of Neural Computing Applications. San Diego, CA: Academic Press Inc., 1990.

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