

Image Cover Sheet

CLASSIFICATION

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131300

**TITLE**NEURAL NETWORKS FOR INDEPENDENT RANGE AND DEPTH DISCRIMINATION IN PASSIVE
ACOUSTIC LOCALIZATION**System Number:****Patron Number:****Requester:****Notes:** Paper #9 contained in Parent Sysnum #129006**DSIS Use only:****Deliver to:** DK

**NEURAL NETWORKS FOR INDEPENDENT RANGE AND DEPTH
DISCRIMINATION IN PASSIVE
ACOUSTIC LOCALIZATION**

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ABSTRACT

Two feedforward neural networks with one hidden layer each were trained using a fast backpropagation algorithm to determine the position of an acoustic source in a waveguide. One network was trained to localize the source in depth while the other was trained independently to localize in range. The output layer consisted of one unit for each possible range or depth of the source. The networks were trained with a signal-to-noise ratio (S/N) of 50 dB and tested with patterns generated with S/N ranging from 0 dB to 20 dB. The performance of the neural networks (NNs) was compared with that of a nearest-neighbor classifier. Evaluation of the processors was done in the context of an estimation problem, i.e. by measuring the root-mean-squared (rms) error of the processors' estimates. The NNs turned out to be less resistant to noise than the conventional processor, but were faster. An explanation is given as to why multilayered feedforward neural networks cannot in general achieve the performances of optimum classifiers.

CONTENT

PROBLEM STATEMENT

NN CONFIGURATION

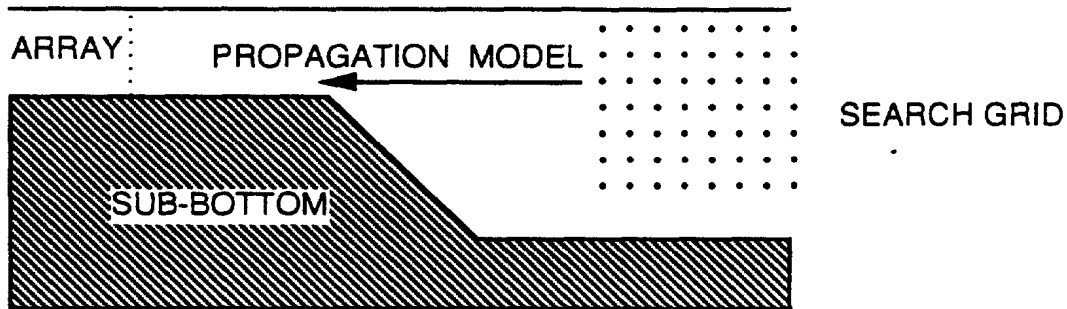
TRAINING ALGORITHM

POTENTIAL AND ACTUAL SPEEDUPS
OVER CONVENTIONAL MFP

ROBUSTNESS ANALYSIS AND
COMPARISON WITH MFP

INTERPRETATION OF RESULTS

MATCHED FIELD PROCESSING



COMPARE MEASURED FIELD AT ARRAY AND
THE ONE PREDICTED BY A PROPAGATION MODEL

DISPLAY GOODNESS OF FIT - AMBIGUITY SURFACE

SEARCH AMBIGUITY SURFACE FOR BEST MATCH

MATCHED FIELD PROCESSING (CONT.) - IMPLEMENTATION DIFFICULTIES

1 - MFP NEEDS A RELIABLE AND ACCURATE MODEL OF SOUND PROPAGATION IN THE OCEAN. SHOULD INCLUDE:

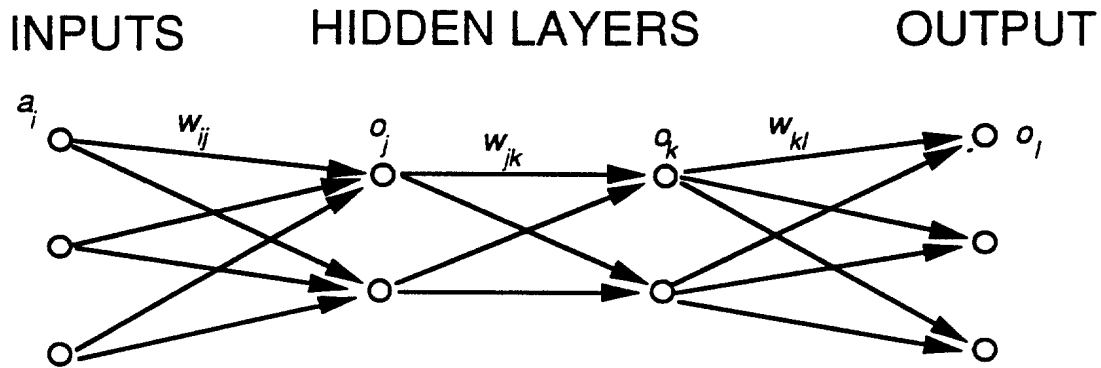
- RANGE DEPENDENT PARAMETERS
- SHEAR IN THE SUB-BOTTOM
- ROUGHNESS SCATTERING
- EXPLICIT 3D

2 - PROPER MODELLING NEEDS DETAILED KNOWLEDGE OF ENVIRONMENTAL VARIABLES, SUCH AS:

- TOPOGRAPHY
- SOUND SPEED PROFILE
- SHEAR SPEED AND ABSORPTION
- ROUGHNESS

3 - MFP SEARCHES ALL POINT IN THE GRID. TIME OF SEARCH AND STORAGE REQUIREMENTS SCALES AS
d · r · a

NEURAL NETWORKS



$$o_j = \frac{1}{1 + \exp\left[-\sum_i a_i w_{ij}\right]}$$

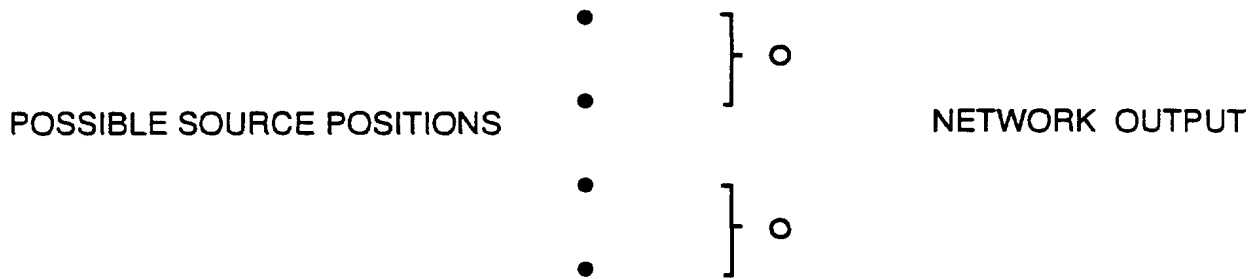
TRAINING:

- IMPOSE TARGET VALUES o_l FOR EACH SET OF INPUTS a_i
- ADJUST WEIGHTS THROUGH GRADIENT DESCENT (BACKPROPAGATION)

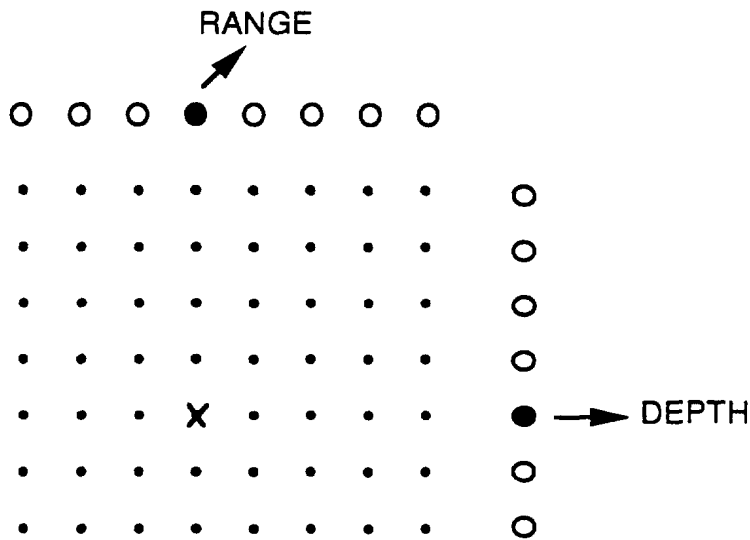
NEURAL NETWORKS (CONT.)

- POTENTIAL ADVANTAGES

- CAN BE TRAINED ON REAL DATA
- CAN BE TRAINED TO GIVE DESIRED ANSWER
 - GENERALIZE OVER SEVERAL DEPTHS OR RANGE



- PROCESS DEPTH AND RANGE SEPARATELY



NEURAL NETWORKS (CONT.) - POTENTIAL SPEEDUP OVER MFP

$$S = \frac{r \cdot d \cdot N_i}{N_i \cdot h + h \cdot N_o}$$

S : SPEEDUP FACTOR

r : NUMBER OF POSSIBLE SOURCE RANGES

d : NUMBER OF POSSIBLE SOURCE DEPTHS

N_i : NUMBER OF INPUTS

N_o : NUMBER OF OUTPUTS

h : NUMBER OF HIDDEN UNITS

TRAINING ALGORITHM

BACK-PROPAGATION

LEARNING RATE ϵ_i INDIVIDUALLY ADJUSTED
FOR EACH WEIGHT

$$\epsilon_i = \epsilon_{i+1} \alpha_+ \quad \text{IF } \text{sign}(\Delta W_{i+1}) = \text{sign}(\Delta W_i)$$

$$\epsilon_i = \epsilon_{i+1} \alpha_- \quad \text{IF } \text{sign}(\Delta W_{i+1}) \neq \text{sign}(\Delta W_i)$$

$$\alpha_+ = 1.1 \quad \epsilon_{MAX} = 50$$

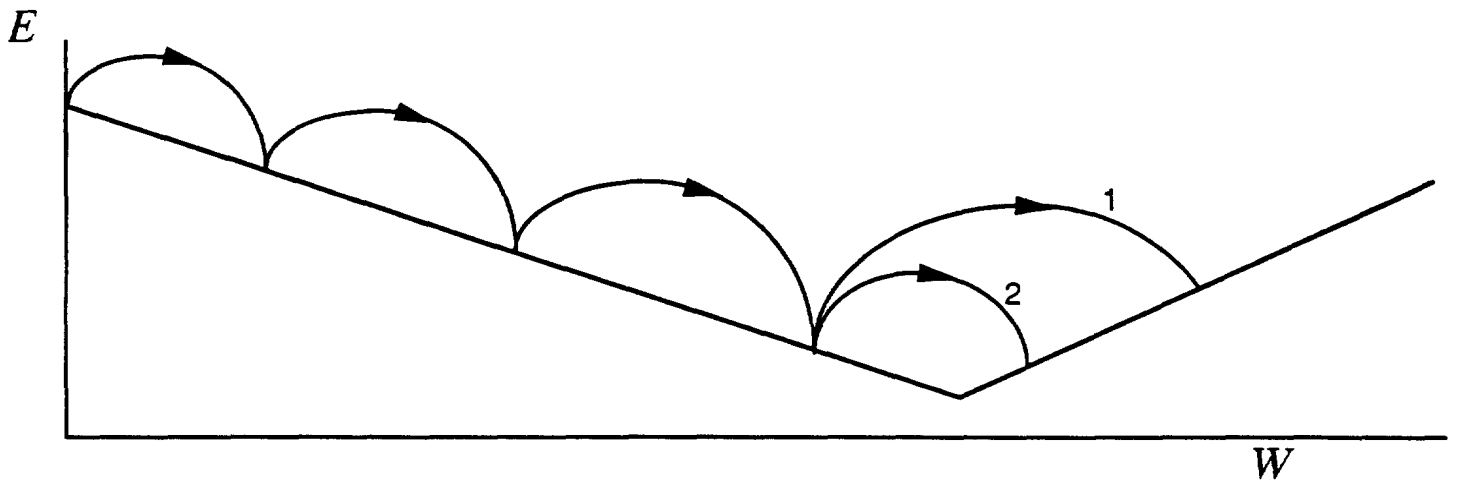
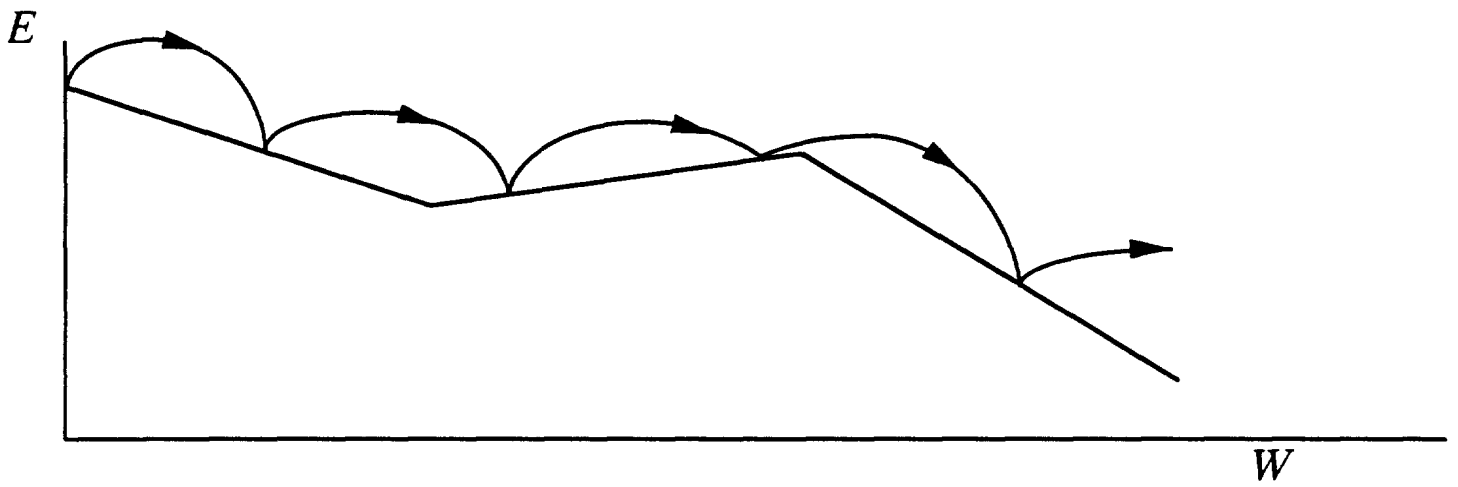
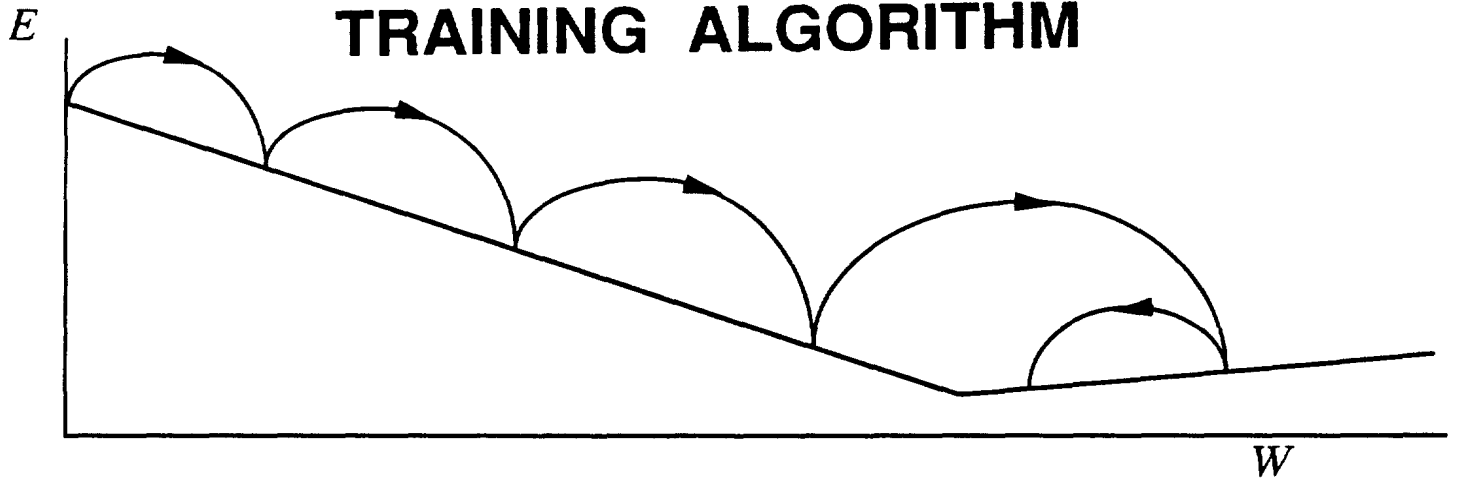
$$\alpha_- = 0.5$$

BACKTRACK IF $E_{i+1} > \beta E_i$ AND RETRY WITH

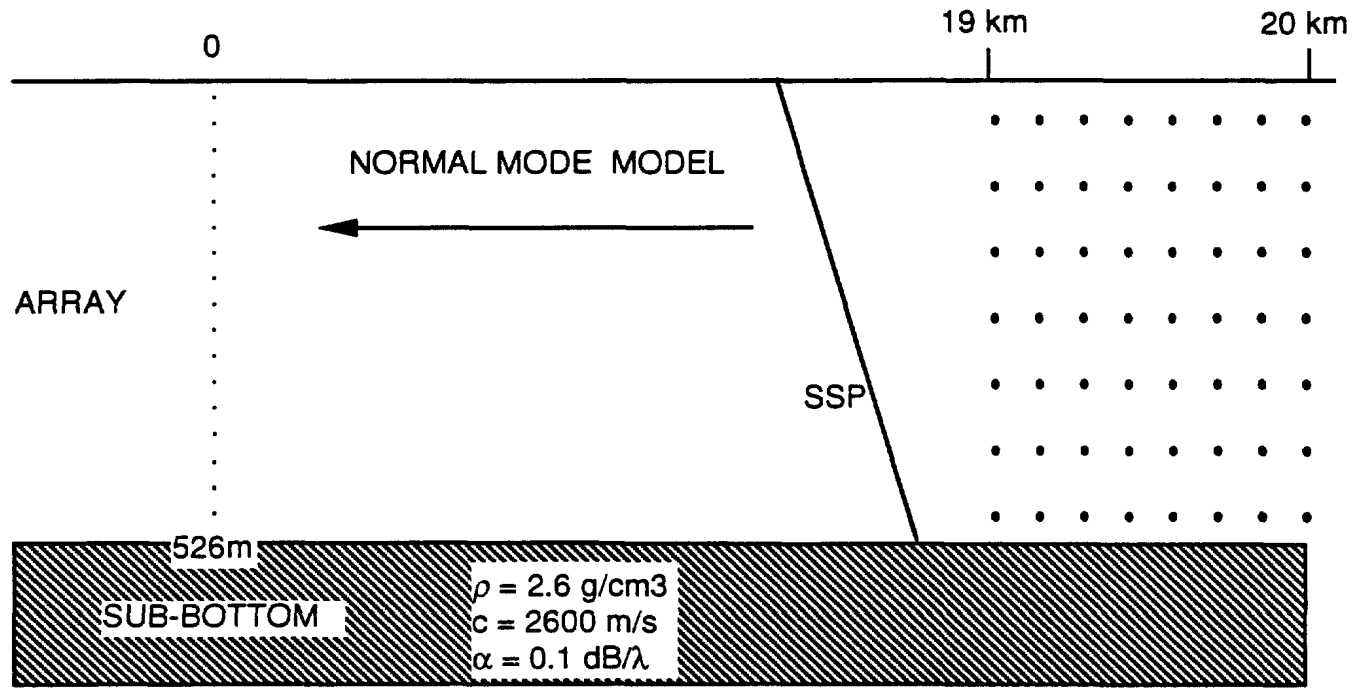
$$\epsilon_i = 0.5 \epsilon_{i+1}$$

$$\beta = 1.1$$

TRAINING ALGORITHM

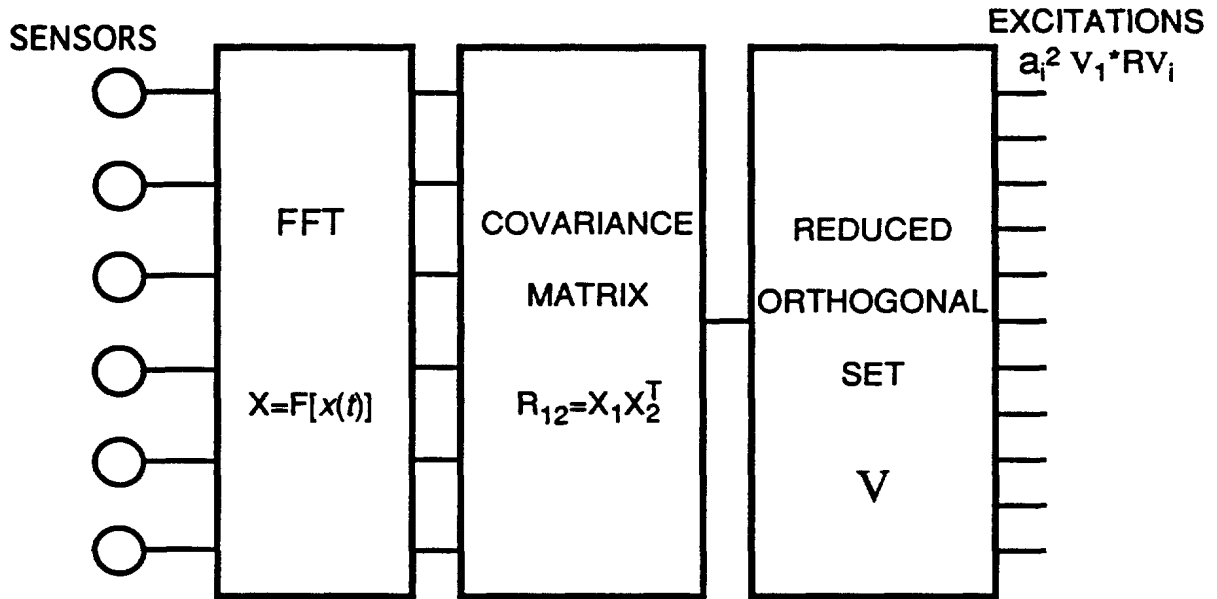


ENVIRONMENTAL MODELLING



SEARCH GRID
22 depths X 11 ranges

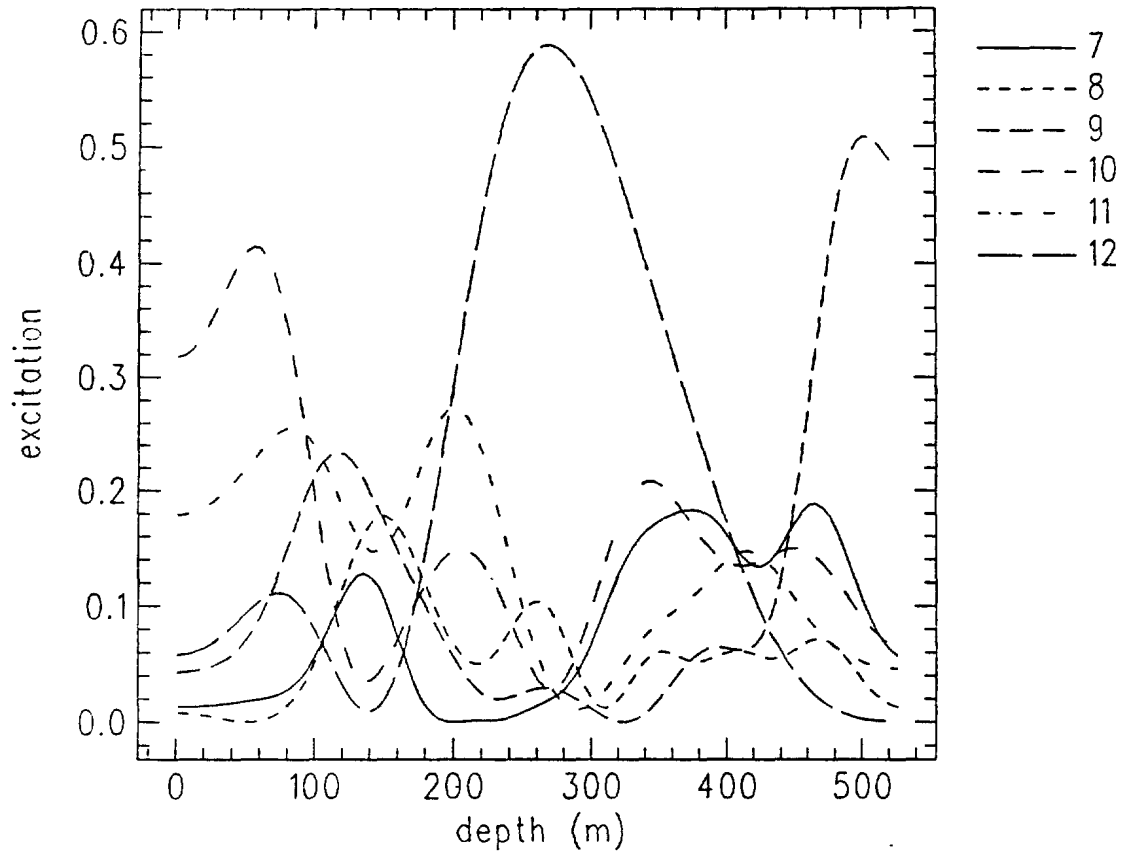
PREPROCESSING



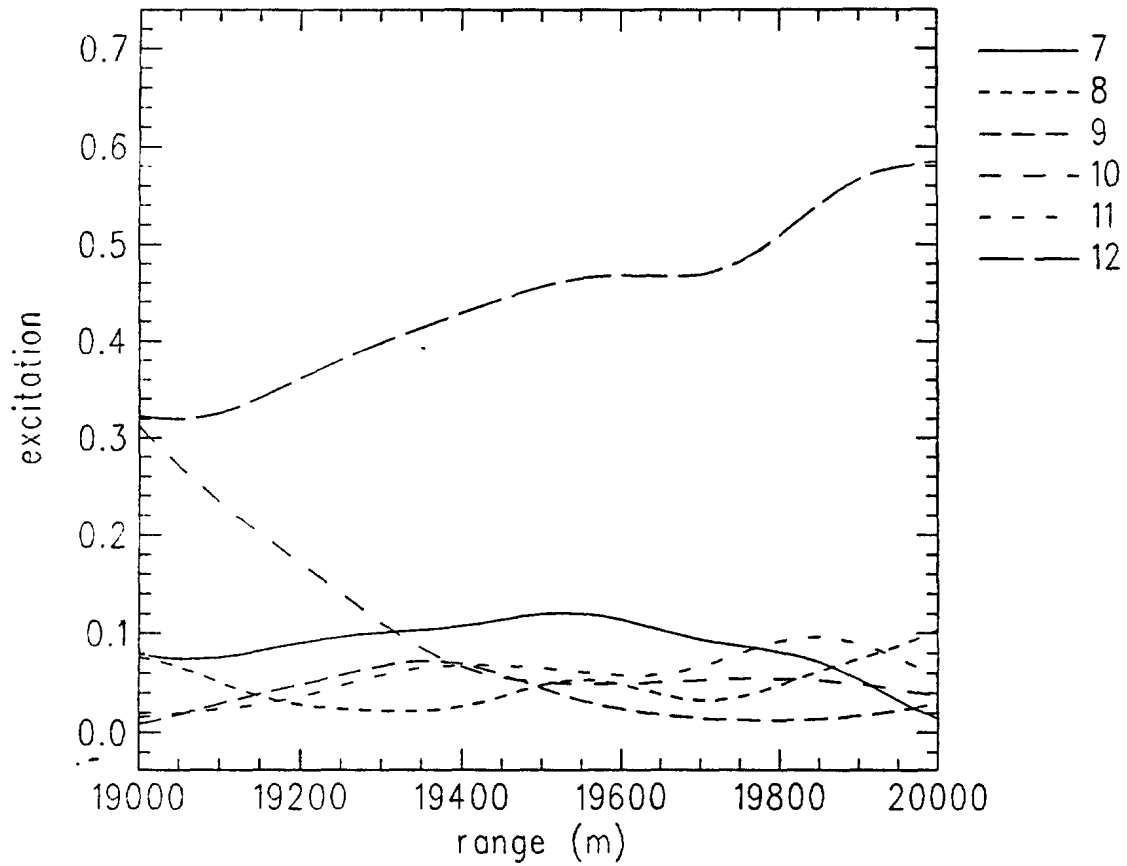
V: eigenfunctions of covariance matrix averaged over all source positions

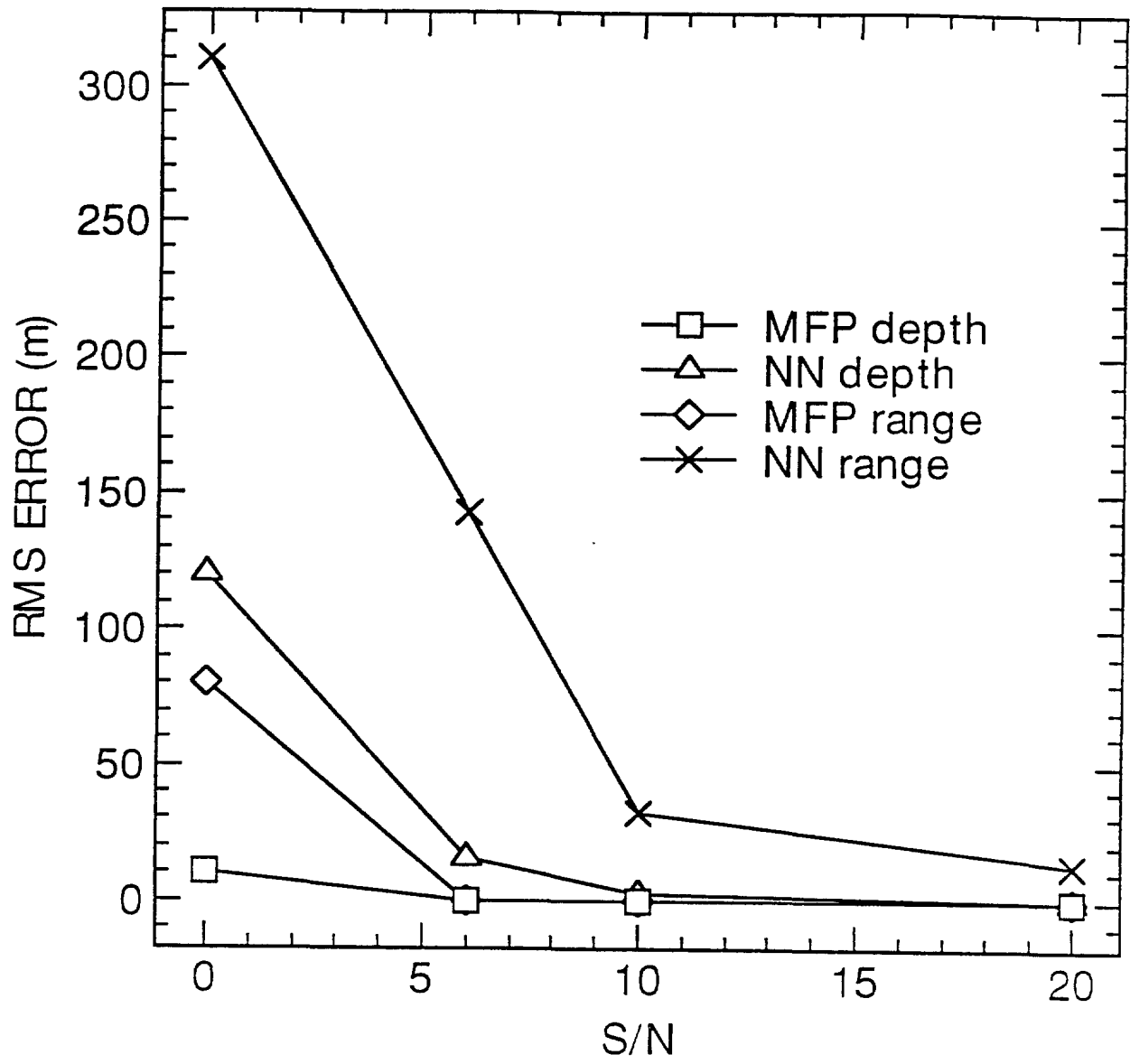
a: excitations of eigenfunctions V for R for a given source position

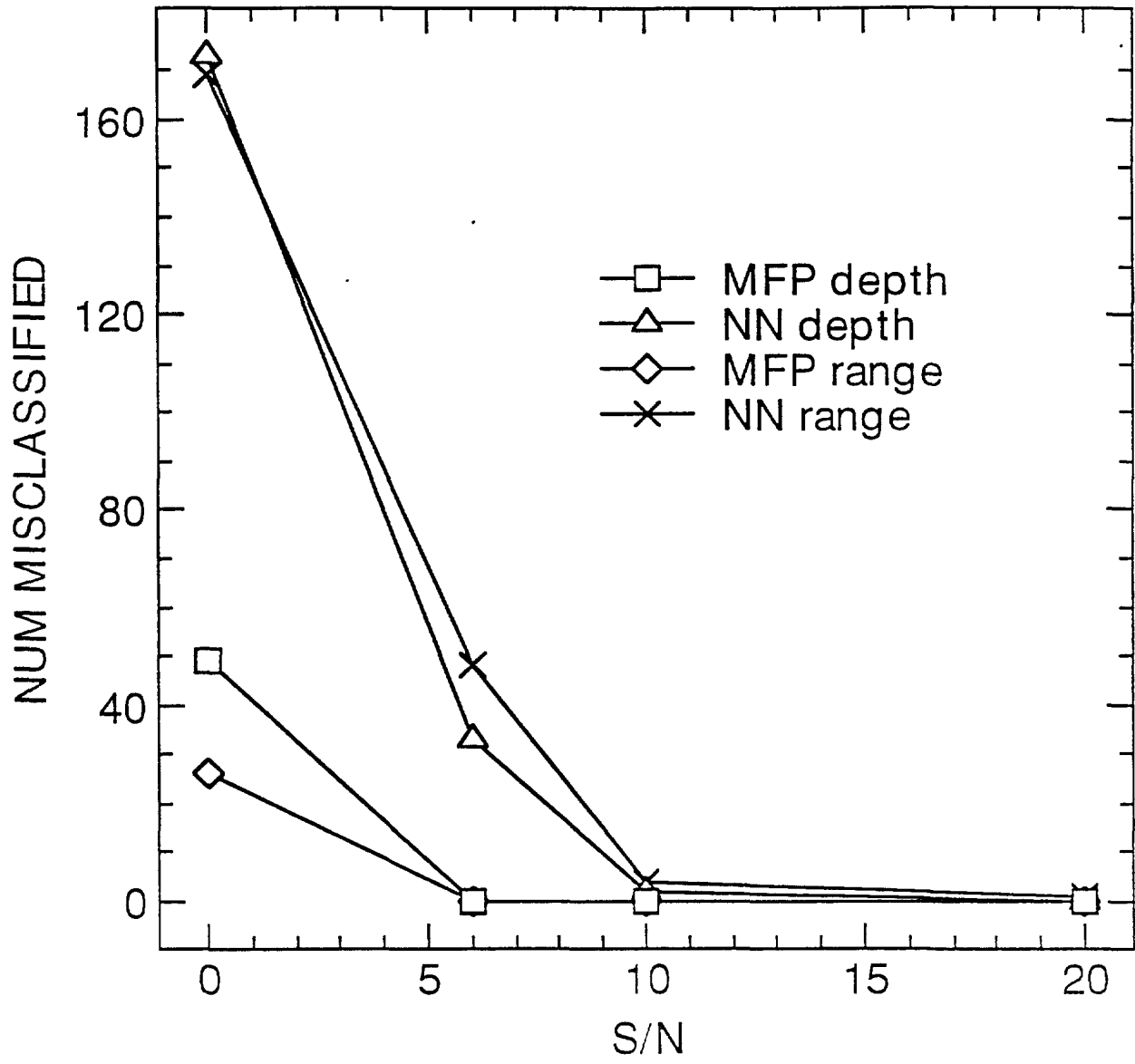
EXCITATION vs DEPTH FOR DIFFERENT EIGENVECTORS



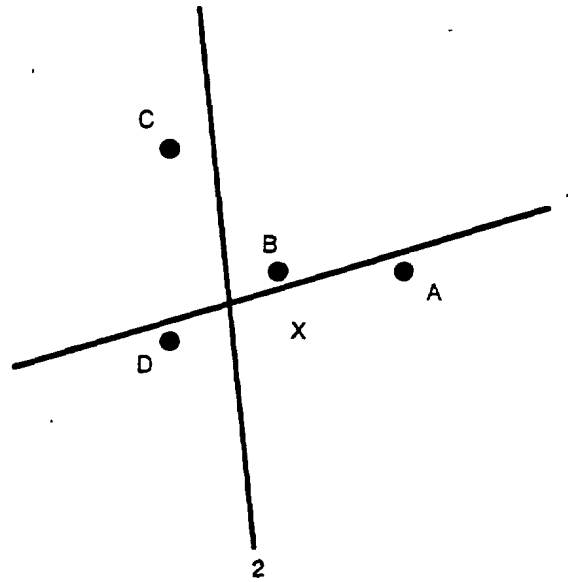
EXCITATION vs RANGE FOR DIFFERENT EIGENVECTORS



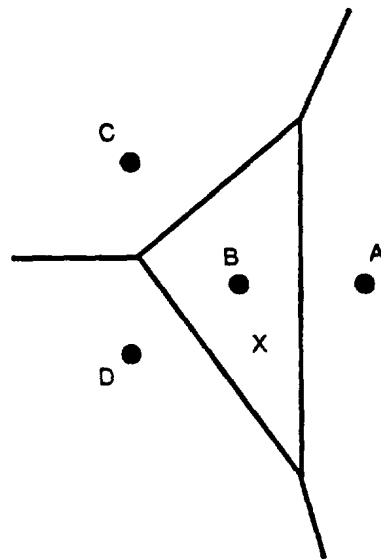




INTERPRETATION OF NEURAL NETWORK DECISION SPACE



INTERPRETATION OF NEAREST-NEIGHBOUR DECISION SPACE



CONCLUSIONS

NNs WERE TRAINED TO LOCALIZE IN DEPTH AND RANGE

THE TRAINED NNs WERE TESTED WITH NOISE

- APPRECIABLE SPEED UP AND STORAGE IMPROVEMENT
- NNs TO BE USED IN HIGH S/N

TRAINING DOES NOT ALWAYS SUCCEED, AND CAN BE VERY SLOW

NUMEROUS LOCAL MINIMA IN TRAINING ERROR SURFACE