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INVESTIGATING THE SEMANTICS OF REMOTE PERCEPTION WITH SIMILARITY ESTIMATES AND MULTIDIMENSIONAL SCALING.

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ABSTRACT

In experimental studies of remote perception the analysis of the resulting data for accuracy and information content has utilized techniques based on rankings by judges and encodings of targets and responses with sets of descriptors. Geographical locations have frequently been used for targets, but there have been few studies which investigate what attributes of such material are preferentially conveyed or how such perceptions are represented. Elucidation of these questions might permit the construction of improved methods of judging remote perception experiments. The analogous problems in normal perception have been investigated by studying the structure of similarity measurements and is the method here applied to the remote perception case. In this pilot study subjects estimated the global similarity between pairs of photographs of geographic locations. The resulting matrix of similarity values was analyzed by multidimensional scaling to give and two and three dimensional representations of the psychological data. A method of estimating the deviation from chance expectation for such data is developed. The results for the remote perception pilot study are compared with structures derived by multidimensional scaling from a comparison study using the same targets normally perceived. The remote perception study shows no deviation from chance by the criterion developed here but the resulting two dimensional semantic structure shows parallels with that from the comparison study and gives weak evidence for the existence of the underlying semantic dimensions of predominately man-made scenes versus predominately natural scenes and the presence versus the absence of land-water interfaces in the scenes.

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1 INTRODUCTION

An extensive literature now exists on a form of communication in which persons acquire significant information about some visual scene with which they have no sensory connection.[2,3,11] Typically such studies will employ target material which is relatively complex and unconstrained in comparison to the smalls sets of symbols like Zener cards used in many earlier parapsychological experiments. Target material in these studies may consist of pictures of geographical locations while the information produced by the subjects comprises more or less fleeting visual, tactile, kinesthetic and other impressions. This phenomenon has suffered from some terminological confusion, being denoted clairvoyance, remote viewing and remote perception by various workers; we shall use the latter term.

A key problem in the study of remote perception revolves around the comparison of the target material with the subject's response. The methods used for the assessment of remote perception data have progressed from matching and ranking by judges to methods based on descriptor sets.[5] The descriptor method has several advantages but has raised the question of whether judging methods could be further improved by designing a descriptor set which was optimized for the semantic structures preferentially available for apperception in remote perception experiments. It may be possible to base the quantification of the information content of transcripts on a small set of underlying semantic dimensions which might serve as "basis vectors" for the subject's internal representation of the target. If such basis vectors could be found, complex constructs in the viewing data might be assembled by combining sets of data so expressed.

Considerable work has been done on solving the analogous problems for visual perception,[3,4,10,16] and a variety of techniques have been utilized for assessing the semantic structures created by a stimulus, with semantic differential scales, adjective lists and similarity estimates being frequently employed. It is possible to extract considerable information from these data, which may be broadly classified as objective, that is related primarily to the target material and subjective, that is related to the internal state of the subject. In particular, work has focussed on assessing the semantics of response to geographic and architectural environments; the field has become known as environmental psychology. In an important paper, Ward and Russell [16] compare several measurement techniques across a set of common stimuli which were pictures of geographical locations. They showed that using semantic differential scales and similarity estimates, it is possible to extract objective information about targets in terms of a small number of semantic dimensions such as predominately natural scenes versus predominately man-made scenes, open scenes versus enclosed scenes and the presence versus absence of land-water interfaces in the scenes. Subjective information is also determinable and examples of this are the affective dimensions of pleasure versus displeasure and arousal versus boredom. The relative subjective information rates of target scenes can also be estimated [10] as can information about preferred behaviors in the presented environment. [16]

1.1 Similarity Methods

Among the various methods employed in these studies, that based on estimates of similarity given by subjects enjoys two advantages. Firstly, there is no linguistic component in the subject's task and therefore no assumptions have to be made about whether the words used in the semantic differential method, for instance, are relevant to the descriptive task or have a constant definition. In the case of remote perception data this might be a substantial advantage since little is known of what representational structures are employed. The second benefit of similarity information is that it exhibits less variance than semantic differential or adjectival methods [16] when the data is reduced to a small number of semantic dimensions.

In a typical study employing the similarity method subjects are presented with all possible pairs of targets drawn from a set of targets. They are required to make a global similarity estimate of each pair of targets on a scale from 1 (very, very similar) to 7 (very, very different). The ordering of presentation is counterbalanced. The resulting symmetric matrices of similarity estimates can be analyzed for intersubject reliability and for a main effect due to the target pairs. Further analysis has used multidimensional scaling (MDS), usually with a Euclidean metric, to represent the similarity data in a space of chosen dimensionality. As a typical example, slides of 20 locations were used as stimuli. [16] The resulting 190 pairs of targets were assessed by 41 subjects. Intersubject reliability was approximately 0.9, a main effect in the data due to the stimulus pairs was found at a level of $p < 0.0001$. MDS analysis in a 5 dimensioned Euclidean space, followed by rotation of the structure, yielded the following dimensions: natural, water scenes versus man-made, land scenes; natural scenes versus man-made scenes; open versus enclosed scenes; natural, open scenes versus man-made enclosed scenes; and natural water scenes versus natural land scenes.

1.2 Multidimensional Scaling

MDS is a technique in which similarity, or dissimilarity data, can be represented in a metric space of chosen dimensionality. The method finds a configuration of points in the given space, one for each of the stimuli, such that stimuli which are adjudged similar are close and ones found different are far apart. Formally, the technique finds a set of points in the given space such that the distances between them are maximally monotonic with the dissimilarity data. The resulting structure can be rotated so as to find dimensions with easily interpretable semantic content. The method takes as input a matrix of dissimilarities, d_{ij}, and attempts to find n points such that the distances between the points, D_{ij}, in the chosen space are such that,

$$S = \frac{\sum_{i \neq j}^{n} (d_{ij} - D_{ij})^2}{\sum_{i \neq j}^{n} d_{ij}^2}$$

is minimized. S is the stress index defined by Kruskal.[6,7] Thus the D_{ij} are as much alike the d_{ij} as possible in a least squares sense. This procedure can be run in a space of any dimensionality for the D_{ij}. Many algorithms have been developed for this purpose; the one used in this study follows that due to Kruskal. This nonmetric MDS algorithm assumes that measurements are nominal or ordinal in character. It is therefore appropriate for the dissimilarity estimates and it has been widely used for this purpose in psychology and sociology. It may be mentioned that the nonmetric algorithm employed in this study produces solutions which are invariant under any monotonic transformation of the input dissimilarity data.

MDS bears some resemblance to factor analysis and principal components analysis. However, MDS is capable of extracting fewer salient dimensions from a set of dissimilarity data than either of these techniques. A further difference is that the two above-mentioned techniques assume that there is a linear relationship between the variables and stimuli and, because of their inherent linearity, these methods tend to overestimate the number of dimensions needed to satisfactorily represent some data. For further details of the algorithm used in the pilot study see Appendix 1.

1.3 An Example of the MDS Analysis of Geographical Data

As an example we take the comparison study described below wherein the 10 targets used in the remote perception pilot study were assessed for similarity by normal perception. Three subjects were presented with all 45 possible pairings of the 10 targets in a randomized order of presentation. Each subject marked the global similarity of the pair of targets on a scale going from very, very similar to very, very different. The estimates from the 3 subjects were averaged to give the following dissimilarity matrix:

Table 1

DISSIMILARITY ESTIMATES FOR COMPARISON STUDY

Target Number	1	2	3	4	5	6	7	8	9
2	5.6								
3	5.9	5.9							
4	8.2	2.6	7.6						
5	4.5	3.0	3.0	4.9					
6	7.5	8.7	7.6	6.3	8.5				
7	5.0	7.8	5.4	5.4	2.8	6.5			
8	8.0	9.1	8.0	7.1	7.6	5.0	3.7		
9	8.3	8.7	6.9	8.3	7.1	2.3	6.6	7.2	
10	9.2	6.5	9.4	6.1	8.4	1.9	9.0	8.2	3.0

Target Number

Plots of the 2 and 3 dimensional MDS solutions for this data are given below.

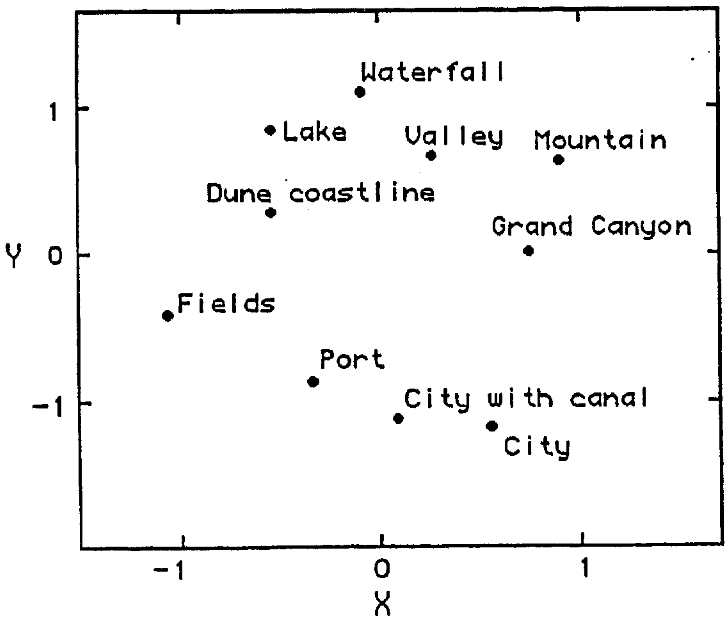

FIGURE 1. PLOT OF 2 DIMENSIONAL MDS SOLUTION FROM COMPARISON STUDY.

In this 2 dimensional solution the Y axis appears to be interpretable as predominately natural versus man-made scenes and the X axis as predominately horizontal versus vertical elements in the scenes.

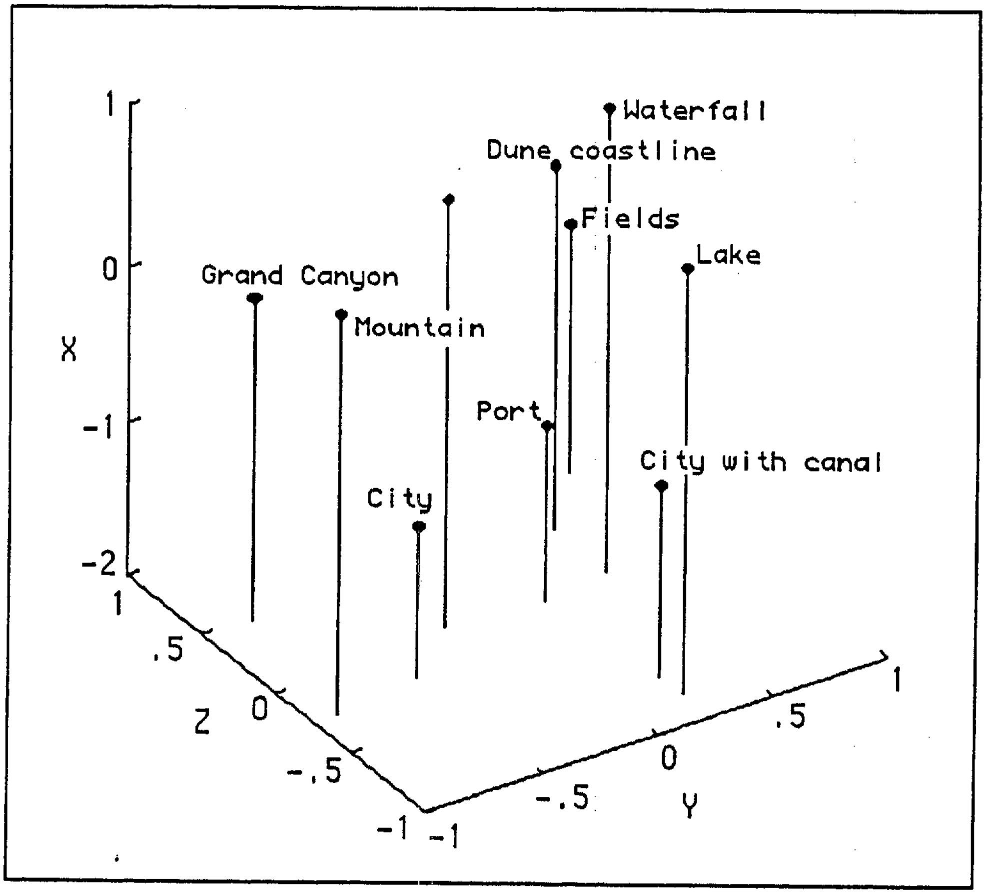

FIGURE 2. PLOT OF 3 DIMENSIONAL MDS SOLUTION FROM COMPARISON STUDY.

This 3 dimensional solution further separates and clarifies the semantic components. Reading from negative to positive, the X axis gives man-made versus natural scenes, the Y axis gives no land-water interface versus land-water interface while the Z axis goes from primarily horizontal images to scenes with strong vertical components. These interpretations are speculative as the data set is very small, but they may serve to demonstrate the method.

1.4 Criticisms of MDS Studies in Environmental Psychology

Tversky has pointed out that it may not be possible to map similarity data into a metric space by MDS or similar methods because psychological similarity data may be incompatible with the assumptions of such a representation.[14,15] He cites the example of similarity estimates of countries;

for instance Cuba might be ranked as globally similar to Russia and globally similar to Jamaica. However Jamaica and Russia would not be estimated as globally similar. Thus the triangle inequality would be violated and therefore no model based on metric spaces can represent this kind of data adequately. Such concept crossing semantic structures may contribute stress to the models presented here. A further problem with similarity data is that examples are easily found which show that similarity is not a symmetric relation. Writing aSb for a is similar to b, that is, $aSb \not\Rightarrow bSa$. Thus distance metrics, for which $D(a,b) = D(b,a)$, will again not adequately represent such data.

Another criticism of environmental psychological models of the kind considered here was raised by Daniel and Ittelson.[1] The structures resulting from MDS of similarity estimates obtained from subjects viewing photographs of locations may be approximately reproduced by replacing the photographic stimuli with terse verbal descriptions of those locations. Little difference to the MDS structure results if subjects are presented with the two statements "Kansas wheat field" and "sunset over a mountain lake" and asked to rate their "global dissimilarity" or whether they are shown pictures of these scenes and asked the same question. It is argued that whenever subjects are required to respond to very diverse environmental settings with unfamiliar, poorly specified, or inappropriate response categories, little or nothing will be learned about the effects of features of the environment on perception or behavior. Instead, there will be a tendency for a priori semantic relationships to emerge, relationships that are only very abstractly related to the physical features of the environment. However, the similarity method does reliably discern the differing targets. For instance target 4 might be far from target 9 in the MDS structure and this might be true whether targets 4 and 9 are presented as short phrases, pictures or visits to the actual locations. The modality of the information obtained by a respondent in remote perception protocols is very variable, a fact that plagues attempts to construct descriptor sets which cover specific and abstract components at the same time. The insensitivity of the similarity approach to this difference might therefore be advantageous in the remote perception context.

1.5 The Assessment of Mean Chance Expectation by Noise Addition and Permutation

Similarity estimates are unusual as parapsychological data in that there is no "correct" answer for the similarity estimate obtained in each trial. How then are such data to be assessed for extra chance effects? An obvious, but inapplicable, method is to examine successive measurements of each d_{ij} for any tendency to clump around one value. This method could not be used in the pilot study since many of the d_{ij} would only have one experimental measurement. An alternative method of finding a chance expectation requires an additional hypothesis. If it is assumed that the dissimilarity estimates obtained from a remote perception protocol do in fact have a structure compatible with a low dimension Euclidean space, then it is possible to compare the stress value of the MDS configuration for the similarity data with stress values from random pseudo-similarity data. This is the method employed in the pilot study. The additional assumption required for this method certainly holds for the type of targets used in the pilot study when assessed for similarity by normal perception, as in the comparison study given here. Whether it remains valid under remote perception conditions is unknown.

To implement this method it is necessary to examine the relationship between stress and the standard deviation of the injected noise. This relationship is also a function of the number of points and the dimension of the space of the calculation. These four parameters, stress, noise, dimensionality of representation and number of points are connected by functions for which closed form solutions are not known. There is also very little numerical work on them in the literature.[12,17] Two methods for evaluating the mean chance expectation (MCE) for stress values from MDS's of dissimilarity data were explored in this study. The first, examined by Young,[17] involves the generation of a dissimilarity matrix by the following method:

1.51 MCE Calculation by Noise Addition

(a) Choose coordinates of m points in a space of n dimensions. Let the coordinates of point i be $\{x^i_j\}$ ($j = 1,\ldots,n$).

(b) To calculate the distance between points i and j perturb the coordinates of points i and j by adding a random normal deviate, R of mean = 0 and chosen standard deviation, to all of the coordinates of each of the points. Then calculate the distance d_{ij} from

$$d_{ij} = \left(\sum_{k=1}^{n} ((x_{ik} + R) - (x_{jk} + R))^2 \right)^{0.5}$$

(c) Repeat (b) till all the d_{ij} are found.

(d) Compute the stress for an MDS solution of the d_{ij} so obtained in an n dimensional space.

(e) Repeat steps (b) through (d) till enough values of the stress have been obtained for the distribution of stress values to be known.

Whilst the above method of injecting noise into a set of coordinates is useful for exploring relationships between stress, noise level, number of points and number of dimensions, an alternative method which gives an exact measure of the mean chance expectation in an experimental context is provided by permutation.

1.52 **MCE Calculation by Permutation.**

(a) Measure a set of experimental dissimilarity measurements d_{ij}.

(b) Compute a MDS configuration for this data in a space of chosen dimension. Let the resulting stress be S_e.

(c) Generate a random permutation of the d_{ij}. That is $d_{ij} \rightarrow d_{kl}$ where k,l are random integers in [1,...,m], where $m = n(n - 1)/2$.

(d) Compute an MDS structure for the permuted matrix. Call the stress for this configuration S_p.

(e) Repeat c and d till enough values for S_p are obtained that the distribution of S_p is well defined.

(f) Compare the experimental stress value S_e with the distribution of S_p's and compute the chance probability by direct integration or other methods.

These methods can be exemplified by taking the data from a normal perception control study of the 10 locational targets used in the pilot study. The following plot shows the effect of adding normally distributed noise to an exact array of 10 points, following the first of the above methods, and also the stress values from permuted matrices from the comparison study in this report.

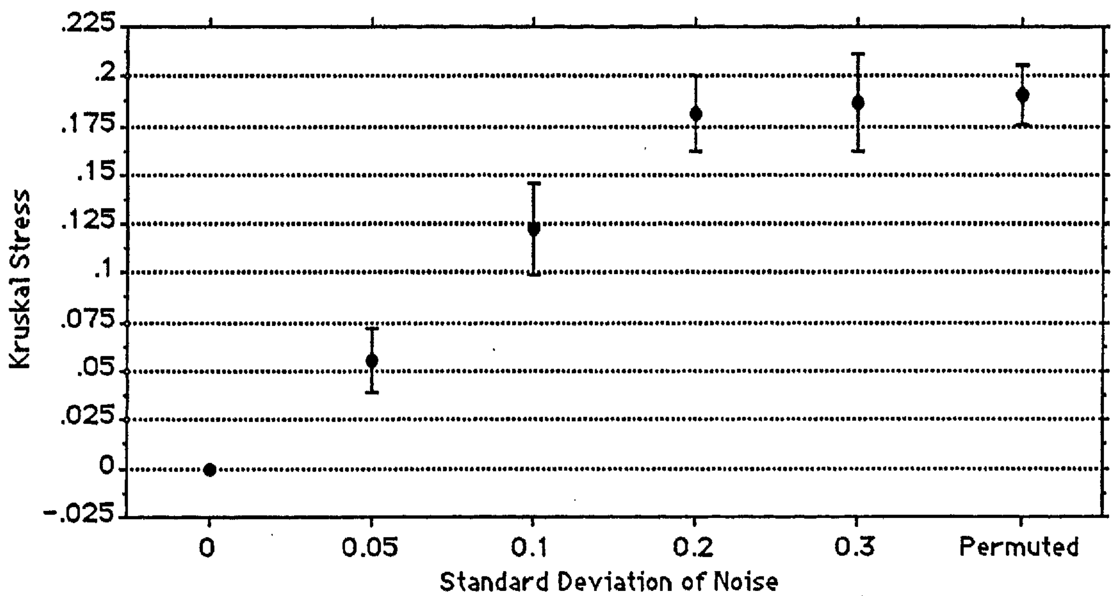

FIGURE 3. PLOT OF STRESS AGAINST TREATMENT OF DATA FOR 10 POINTS.

As can be seen, the two methods give close agreement for the chance level stress value for this number of points in a 2 dimensional representation. The same exercise can be repeated for other numbers of points. For instance with 13 points in 2 dimensions:

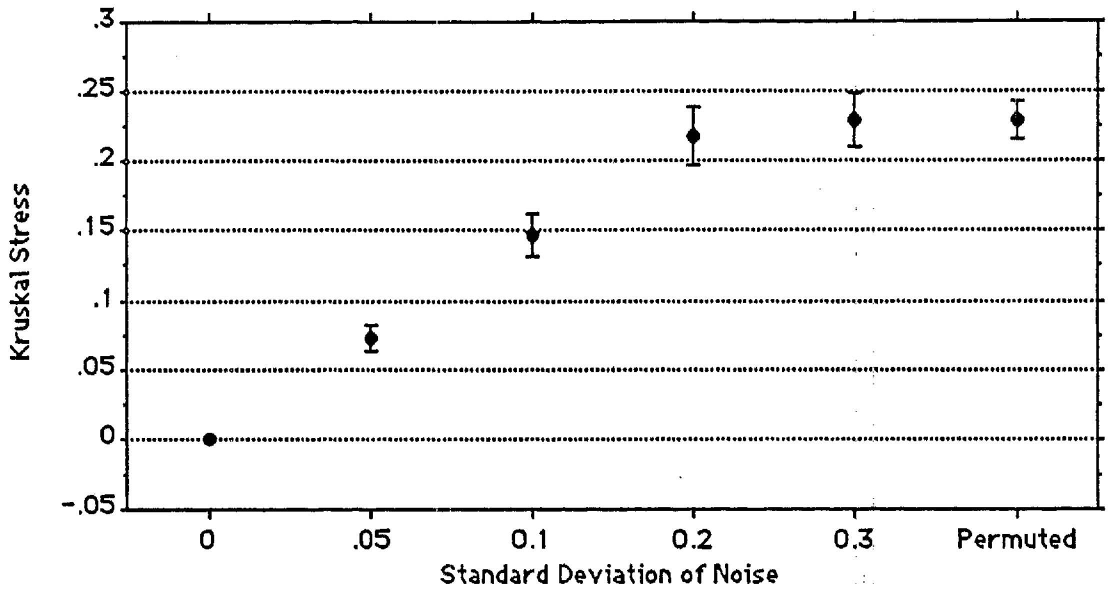

FIGURE 4. PLOT OF STRESS AGAINST TREATMENT OF DATA FOR 13 POINTS.

As can be seen from the above, it is possible to use the permutation method to distinguish extra chance similarity values in the pilot study, or similar experiments, always providing that the additional assumption of low stress structure in the noise free data is assumed. It can also be seen that as the number of points in the configuration is increased the magnitude of the chance expectation stress increases whilst its variance decreases. Thus for a given experimental stress value, the Z-score of the stress value will be larger the greater the number of points. However, in designing a remote perception study one would like to use the minimum number of points so as to reduce the necessary number of trials. The number of trials is, of course, proportional to the square of the number of points. The question therefore arises what minimum number of points is required to establish a structure. Young[17], continuing investigations by Shepard, shows that the accuracy of the metric data recovered from an MDS of noisy data increases as the number of points increases, and varies inversely with the increase in error and with the number of dimensions scaled. Young's data show that with 10 points a 2 dimensional structure can be recovered with 72% accuracy of the original distances, or dissimilarities, in the presence of a normally distributed error of standard deviation one half of the standard deviation of the true distances in the configuration. Metric recovery of 3 dimensional structure is 68% under these conditions which require 45 similarity values to be estimated. A 10 target set was therefore chosen for the pilot study as a compromise between the desire to increase the number of points allowing for good metric recovery and tightly distributed MCE stress values and the requirement to keep the number of similarity values to be measured small.

This analysis can be extended to the case where part of the similarity matrix is unmeasured and where those elements lacking an experimental value are filled by the mean value of the matrix elements. In this circumstance, investigation has shown that the variance of the stress values of the permuted matrices is increased and thus a given low value of stress from experimental data will have a reduced Z-score with respect to the broadened chance distribution. However experiments have shown that the method is quite tolerant to missing data and provided that less than 30% of the matrix elements are lost, the recovered 2 dimensional structure (with 10 data points) is usually close to the structure derived from the full similarity matrix.

2 PILOT STUDY

The aim is to collect dissimilarity estimates for pairs of targets from a set of 10 photographs of geographical locations in a remote perception protocol and analyze these by multidimensional scaling.

As this study is very much conceived as exploratory in nature there are no formal null hypotheses. Similarity data has never before been obtained in this experimental setting and therefore it is unclear what results may be produced. However, by analogy with the MDS studies of similarity data of geographical stimuli discussed above, it may be expected that the MDS structure resulting from the similarity estimates obtained through remote perception will show a stress below that expected by chance. The chance expectation value of the stress will be calculated by the permutation method described above; the experimental values for dissimilarities will be randomly permuted and a chance expectation distribution of stress values thereby found. The experimental stress will be compared to this distribution. Two and three dimensional MDS analyses will be so performed.

2.1 Method

The set of 10 targets used in the pilot study require the measurement of 45 quantities for the matrix of similarities. Owing to the necessity of keeping the subjects blind to the target pair used in each trial it was necessary to choose the target pair for each trial by random selection from the whole set of 45 pairs. Using the pool without replacement would otherwise have been preferable, since then 45 trials would have guaranteed that each target pair had a trial assigned to it. For the utilized method of selection with replacement, the planned 45 trials for each subject would give a fair chance of 80% coverage of the similarity matrix for the combined subject data. Since we are trying to ascertain 45 continuous numerical quantities with the very noisy remote perception channel, many more trials than this would be preferable.

To the author's knowledge, this experiment breaks new ground in remote perception protocols in several ways and some aspects of it appear problematic. Firstly subjects are required to produce descriptions of two targets in each trial before feedback is presented. The success of the method depends on their ability to produce some accurate information to both targets in each trial; successful description of only one will not suffice as there will be no information on which to base the similarity estimate. Secondly, the subjects become familiar with all the 10 targets after a few trials and this complicates their task because of their propensity to fixate on one of the targets from memory rather than the fleeting, and often incomprehensible, imagery thought to constitute ideal remote perception data. Both these effects were hopefully ameliorated by encouraging the subjects to limit the time of their efforts to an absolute minimum and to produce extremely sparse transcripts of the two targets. Subjects were requested to cease their remote perception effort as soon as they felt they had some visual material and an overall gestalt of the scene. Another concern was whether the subjects would be able to correctly assign the remote perception information to each target in a trial. If some of the perceptual elements were to be mixed between the targets, the pair might be judged over-similar. If there was a consistent bias of this kind across the experiment, all the similariy estimates would be biased towards excessive similarity and the resulting MDS structure would be unchanged, since the structure is invariant under monotonic transformations of the experimental data. However, the effect might not be so consistent. Also it is possible that the order of the transcripts might not correspond to the target order; in other words the first transcript produced might refer primarily to the second target and vice versa. This should not effect the similarity estimate and hence the MDS analysis.

2.2 Subjects.

Two subjects were chosen for this pilot study; each being male and in their thirties. One, AV, had considerable experience of remote perception experiments. The other, DK, had not previously taken part in any formal parapsychological studies, but was of the belief that he could successfully remotely perceive targets. The purpose of the experiment in elucidating the semantics of remote perception was explained to both participants and both appeared highly motivated to have the experiment succeed.

2.3 Targets.

In selecting ten scenes of geographic locations for the pilot study, several criteria were used:

(a) To use targets which were similar to those in use at SRI International so that compatibility of the database would allow conclusions to be drawn from the pilot study which would find application at SRI. It was thought that the data from the pilot study might be analyzed by a descriptor set method and a comparison drawn between the estimated similarities from the pilot study and the encoded transcripts.

(b) To include in the set several pairs which would have been judged fairly similar, and several very different, on the basis of Ward and Russell's [16] results. On the assumption that similarity estimates derived by remote perception approximate those derived from perceptual studies, this would ensure that the target set for the pilot study would have target pairs at the extremes of the similarity - dissimilarity axis. In the low signal to noise ratio regime of remote perception studies this maximizes the possibility of an extra-chance result.

(c) To include targets at the extremes of the semantic dimensions found in normal perception similarity studies of geographic locations.

Table 2.
TARGET POOL FOR PILOT STUDY.

Pilot Study Target No.	SRI Target Number	Target Short Name	Target Description
1		Waterfall	Waterfall, dark vertical rock, trees.
2	393	Mountain	Vertical rock and snow fields. Dark sky.
3	323	Mountain Lake	Blue crater lake, snow, clouds, small cliffs.
4	414	Grand Canyon	Many jagged pinnacles, all yellow and brown.
5	334	Valley	Deep U shape, mountains, woods,snow,river.
6		Port	Harbor, city buildings, boats.
7	447	Dune coastline	Wind sculpted dune field, slopes to beach, sea.
8	401	Fields	Flat Kansas fields, rectilinear pattern, church.
9	334	City with canal	Canal, city with skyscrapers, bridge.
10	382	City	Old European city, church spires, hills.

The pilot study targets include three city scenes, and six scenes where there is little evidence of man-made activity. Also present are six scenes with water (either rivers or shoreline) clearly visible and four with no water present. Thus the set includes several targets which would probably be adjudged similar and several which are very dissimilar as well as targets which are at the extremes of the man-made versus natural and land-water interface versus no land-water interface semantic dimensions. The ten targets chosen for the study were identified from the large collection of pictures of geographical locations at SRI. The pictures give a wide view over the scene and some of them appear to be side looking aerial shots. All were reproduced onto color photographic prints of 20cm. x 25cm. size.

2.4 Target Selection Method

A program was written in FORTRAN to control the target selection in the experiment. This program incorporated a pseudo random number generator algorithm due to Lewis & Payne.[8] The output of the implementation of their algorithm used in this experiment was checked against values given in the cited reference to ensure correct functioning. The algorithm uses the feedback shift register method and has been extensively checked for randomness.

The random number generator was seeded once at the beginning of the study prior to the first trial. Thereafter all targets pairs were determined by this choice; the targets for a given trial being unknown to the experimenter and subjects until that trial's completion. This method of target selection was adopted in order to reduce any effects of intuitive data selection due to the experimenter.[9] With the method used here only one decision point occurred in the entire experiment (rather than one decision point for each trial) and consequently the opportunity for fortuitous target selection by paranormal selection on the part of the experimenter was largely eliminated.

In each trial the subjects were given the following instructions:

"You are required to do two precognitive remote viewings on two target pictures. These pictures are of geographical locations somewhere around the world. The viewings will be rather quick and the aim is to perceive a few of the most salient features of the locations. You are encouraged to make drawings and verbal comments. It is suggested that you might describe the first target for approximately five minutes, take a short break and then describe the second target for a similar period. You will then be asked to mark your estimate of the similarity of the two targets on a scale as below:

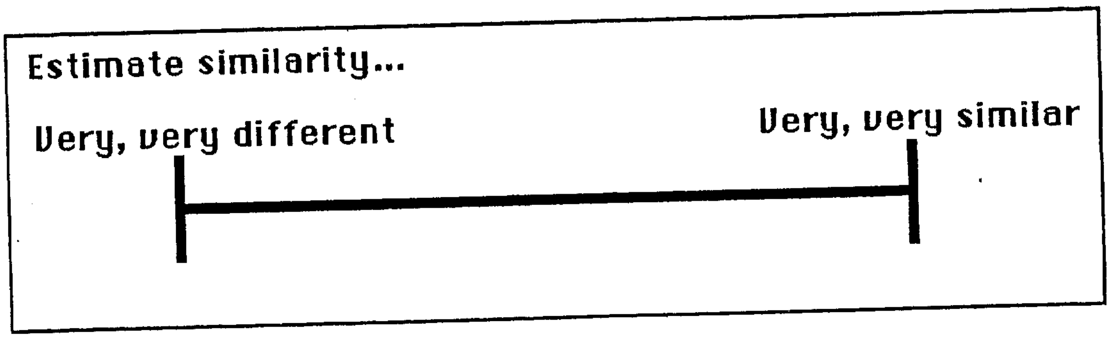

FIGURE 5. SCALE FOR SUBJECTS TO INDICATE SIMILARITY ESTIMATE.

Immediately after this you will be shown the first of the two targets and allowed to examine it. A minute later the second target will be shown. This completes the trial. It is hoped that we can complete two, or perhaps three, trials per session."

Each trial took approximately 30 minutes and followed the above sequence. Subjects made drawings with written comments for each target description and took a break of approximately 5 minutes between remote perception efforts on the two targets. There was no delay between the end of the second remote perception and the entering of the similarity estimate which was then followed by immediate feedback to both targets. The position of the mark made on the scale by the subject was read off on a separate scale in which "very, very different" corresponded to 10 and "very, very similar" to 0. The scale was read to one decimal place.

2.5 Results

Owing to limitations of experimental time only 65 of the planned 90 trials were completed. One subject, AV completed 35 trials giving values for 24 of the 45 matrix elements, while the other subject DK completed 30 trials which also gave 24 measured matrix elements. In order to examine the data from both subjects together, each subject's dissimilarity estimates were normalized to unity standard deviation and mean of 5 and then these readings were averaged to give a dissimilarity matrix for both subjects combined. In this matrix, 36 of the 45 elements had experimentally determined values. In all these matrices unmeasured elements were filled with the mean of the remaining matrix elements. Owing to the random target selection method, some matrix elements in the combined matrix had 4 separate trials, whilst for 9 elements there was no experimental reading obtained.

Given the reduced number of trials, the MDS analysis is only really valid for the combined matrix of both subject's data; the dissimilarity matrices for the separate subjects have 46% of the values missing and under these conditions, given the noisy data, there is no likelihood of recovering structural information. Nevertheless, for completeness, the 2 dimensional scaled solutions are given for the separate subject data.

The three matrices of dissimilarity values, from each subject separately and from the two combined, were permuted 25 times and the new matrices scaled. The stress values obtained from these permutations were used to provide an estimate of the mean chance expectation for stress and a T-test was applied to determine if the stress values for the experimental dissimilarity matrices were significantly different from chance expectation.

Table 3

STRESS VALUES FOR MDS MODELS OF THE PILOT STUDY.

Subject	Model Dimension	Experiment Stress	MCE Stress	Probability 1 Tailed
AV	2	0.137	0.12	0.76
DK	2	0.137	0.132	0.58
BOTH	2	0.184	0.185	0.5
AV	3	0.055	0.052	0.6
DK	3	0.077	0.055	0.9
BOTH	3	0.096	0.1	0.38

These stress values do not differ significantly from chance. The values for the separate subjects are higher than mean chance expectation, in the opposite direction to that hypothesized. This may be due to the very high proportion of values in these matrices being mean values inserted to cover cases where no experimental data was obtained. Given the small number of trials in relation to the 45 data points in the dissimilarity matrix it is unsurprising that these chance level stress values occurred. The stress value, 0.14, of the comparison study described below is plausibly a minimum for the stress which might be observed in the remote perception case. Noise added to the measured values of the dissimilarities would increase the observed stress from this value towards the mean chance expectation value derived from permuted dissimilarity matrices.

In spite of the high observed stress values in the pilot study, it is possible that the resulting MDS structures will show organization which can be semantically interpreted. The 2 dimensional structures for the combined subject data and for each subject separately are given below.

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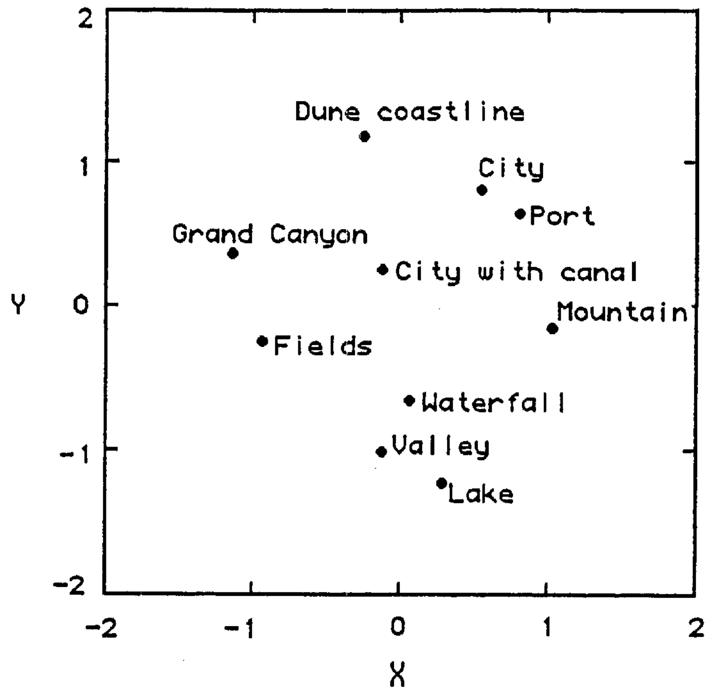

FIGURE 6. 2 DIMENSIONAL MDS STRUCTURE FROM BOTH SUBJECTS COMBINED.

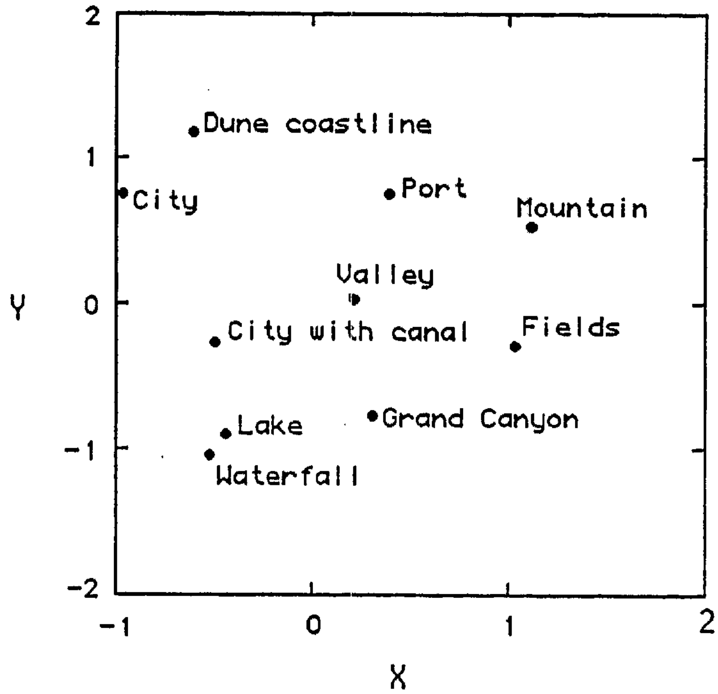

FIGURE 7. 2 DIMENSIONAL MDS STRUCTURE FROM SUBJECT AV.

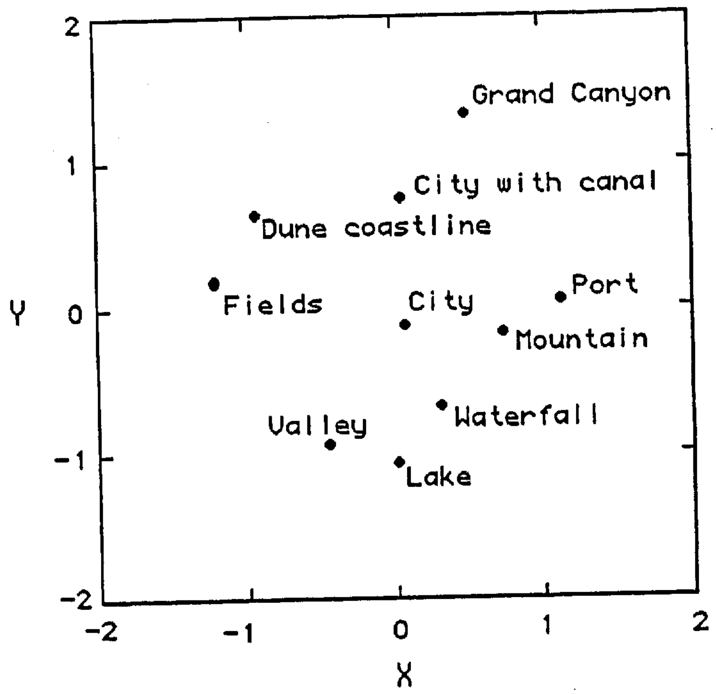

FIGURE 8. 2 DIMENSIONAL MDS STRUCTURE FROM SUBJECT DK.

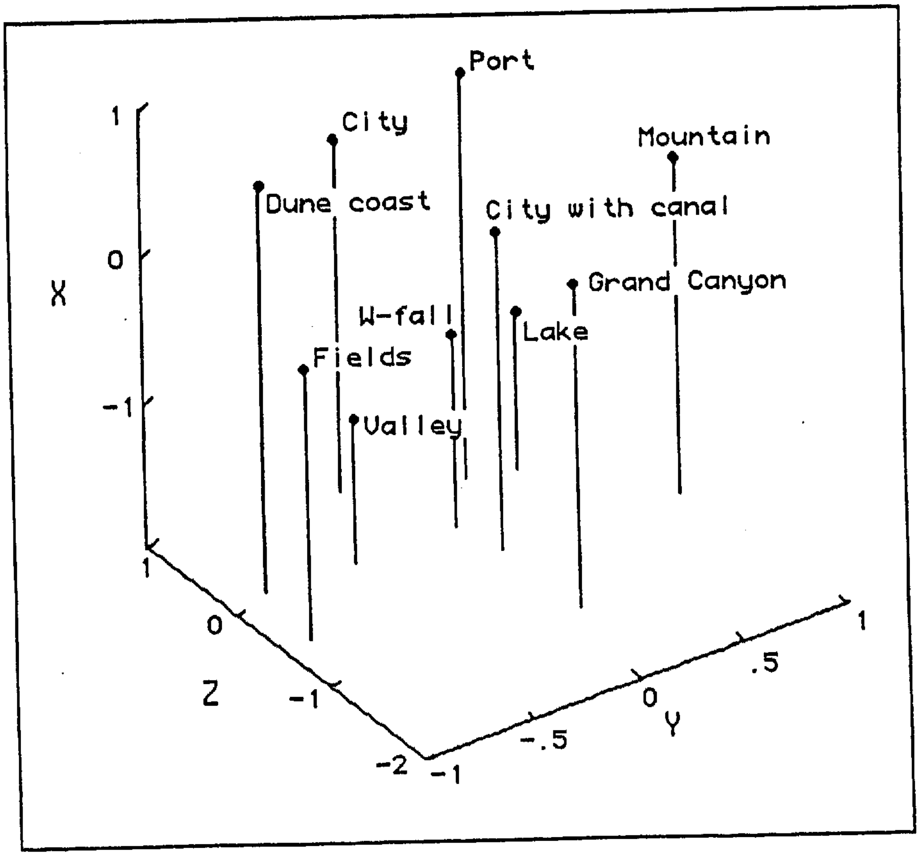

FIGURE 9. 3 DIMENSIONAL MDS STRUCTURE FROM BOTH SUBJECTS COMBINED.

As can be seen from Figure 6, the data from the subjects combined has resulted in a MDS structure which appears to group the valley, waterfall and lake targets, all of which have prominent land-water interfaces visible and are predominantly natural. However the dune coastline target also meets these criteria and this is not in the same grouping. The urban scenes, the city, port and city with canal targets, are also fairly close in the combined subject structure. We may therefore conclude that there is weak evidence visible in this similarity data of discrimination of scenes containing land-water interfaces from those without and between natural versus man-made scenes. The 3 dimensional structure for the combined subject data given in Figure 9 also appears to group the urban scenes, but there is little evidence of interpretable structure. These differentiations have not been tested statistically, but it appears that more data of higher quality would be required to confirm them.

3 COMPARISON STUDY

In order to be able to compare the similarity values and semantic structure seen in the pilot study with the corresponding data obtained by normal perception, a small study was performed using the same target material, but unfortunately not the same subjects, as in the pilot study.

3.1 Method

Three subjects, all of whom had participated in other studies of remote perception but who otherwise had no connection with this study participated. The subjects were requested to give a global rating of similarity or difference on the scale shown in Figure 5 for all 45 pairs of the 10 targets used in the pilot study. In a session of approximately one hour the subjects viewed the pairs of color pictures at one meter distance and made a mark on the scale giving the perceived similarity. The target pairs were presented in a random order.

3.2 Results

The dissimilarity ratings are given in Table 1 and the resulting 2 and 3 dimensional MDS structures in Figures 1 and 2 respectively. The stress values were compared with those obtained by permuting the experimental dissimilarity matrix randomly and computing an MDS structure exactly as in the pilot study. Using 25 permutations to give chance stress estimates, the following statistics were derived.

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Table 4

STRESS VALUES FOR MDS MODELS OF THE COMPARISON STUDY.

Model Dimension	Experiment Stress	MCE Stress	Probability 1 Tailed
1	0.28	0.37	0.03
2	0.138	0.186	0.03
3	0.07	0.102	0.03

These stress results confirm that the similarity estimates produced in this experiment are significantly structured. The resulting 2 and 3 dimensional MDS structures are interpretable in terms of discrimination occurring due to man-made versus natural features and the presence or absence of land-water interfaces and possibly pronounced vertical topography (see Section 1.3).

4 CONCLUSION

In this report we have described a novel method for investigating the semantics of remote perception. The method appears to have merit in terms of its potential ability to discriminate aspects of remote perception targets which may be preferentially perceived in this context. Therefore the method may find use in the development of judging methods both by providing information on which descriptor sets design can be optimized and also by judging remote perception efforts by similarity estimates directly.

It is clear that the pilot study presented here has provided only very weak evidence of the discrimination of targets by similarity estimates. However, given the large amount of quantitative data required for the reliable determination of semantic structures and the unreliability of remote perception, it might be expected that such a small study is unlikely to give clear results. Given a data set an order of magnitude larger, useful results might well emerge.

5.1 Appendix 1

The MDS algorithm used in the pilot study follows that due to Kruskal. [6,7] The program begins by computing an initial configuration of points whose configuration is a linear function of the input data. This is achieved by by a metric MDS method in which missing values in the input dissimilarity matrix are replaced with the mean value of all elements of the matrix. Then the values are converted to distances by adding a constant. A scalar products matrix B is then calculated by following the procedures in Torgerson. [13] The initial configuration matrix for the non-metric MDS is then found from the eigenvectors of B using the Young-Householder procedure. Nonmetric optimization then proceeds by iterating the following sequence of steps: at the beginning of each iteration the configuration is normalized to have zero centroid and unit dispersion. Next, Kruskal's DHAT (fitted) distances are computed by a monotonic regression of distances onto data. The stress, S, is calculated and checked for whether it has decreased sufficiently from the last iteration. If it has not, the negative gradient is computed for each point by taking the partial derivatives of stress with respect to each dimension. Points in the configuration are moved along their gradients by steps proportional to the derivatives and the next iteration starts. After the last iteration the configuration is shifted so that its centroid lies at the origin so that it has unit dispersion. For further details, see Wilkinson [18] and the cited references.

5.2 Appendix 2

DATA FROM PILOT STUDY. DISSIMILARITIES NORMALIZED TO UNITY STANDARD DEVIATION AND MEAN OF 5.

Trial	Subject	Targets	Dissimilarity	Trial	Subject	Targets	Dissimilarity
32	AV	2 1	5.438	26	AV	7 6	5.541
40	DK	2 1	4.221	43	AV	7 6	4.458
9	AV	3 1	3.219	29	DK	8 2	5.182
2	DK	3 1	4.322	15	DK	8 3	5.991
23	AV	3 2	5.541	38	AV	8 5	4.509
56	DK	4 1	5.789	22	DK	8 5	4.272
39	DK	4 3	5.182	57	DK	8 6	6.193
13	DK	4 3	5.233	10	AV	8 7	6.108
30	DK	4 3	5.485	65	DK	8 7	3.210
51	DK	5 1	3.058	54	AV	9 1	3.684
8	AV	5 3	4.819	63	DK	9 2	4.727
14	DK	5 3	3.210	37	AV	9 3	3.116
5	DK	5 4	6.648	33	AV	9 3	5.593
41	AV	5 4	4.458	61	DK	9 3	6.244
27	AV	6 1	5.386	59	AV	9 4	3.735
47	AV	6 2	3.942	24	AV	9 5	6.108
7	DK	6 2	3.614	58	AV	9 5	4.303
52	DK	6 3	5.233	28	AV	9 7	3.735
1	DK	6 3	5.688	34	AV	9 7	5.438
50	DK	6 4	5.384	3	AV	10 1	5.696
21	DK	6 5	4.778	53	AV	10 1	5.696
45	DK	6 5	5.283	11	DK	10 1	3.159
19	DK	7 1	6.244	17	AV	10 2	6.418
42	AV	7 2	4.716	64	AV	10 2	6.057
62	AV	7 2	5.335	4	AV	10 5	5.335
36	AV	7 2	5.696	55	AV	10 6	3.632
12	AV	7 3	6.366	35	AV	10 7	4.406
20	AV	7 4	6.728	16	AV	10 7	6.366
18	DK	7 4	4.980	25	AV	10 7	3.735
31	AV	7 5	4.354	67	DK	10 7	4.778
46	DK	7 5	6.042	44	AV	10 8	5.335
66	DK	8 5	5.334	6	DK	10 8	4.778
				60	DK	10 8	5.738

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