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Selecting Band Combinations from Multispectral Data

The procedure provides a single preferred choice, decided uniquely by the statistics of a scene or subscene, and taking full account of any correlations that exist between different bands.

Abstract: *The question of selection of band subsets from multispectral image data, with particular reference to the choice of color combinations from Landsat-4 Thematic Mapper data, is addressed. An algorithm for band subset selection is provided, and a relationship to multispectral image entropy is established.*

Introduction

The problem of selecting N-band subsets from P bands of multispectral data is an old one, but it has become particularly relevant now that data from the Landsat-4 Thematic Mapper (TM) are in widespread use (Williams, 1984; Chavez *et al.*, 1982; Chavez *et al.*, 1984). Because the human eye employs three primary colors, and the Thematic Mapper returns seven bands of data, one problem that inevitably arises is that of making the most effective three-band color composite images. The choice is non-trivial, because three bands can be selected from seven in 35 ways. Also, any band can be assigned any color. This gives a total of 210 different possible color presentations of TM three-band images.

In this paper a general logic is presented for selecting N bands from $P(>N)$ bands of image data. For convenience of presentation, the discussion is given mainly in terms of selecting a three-band set from the seven bands of TM. However, the method is quite general. The procedure provides a single preferred choice, decided uniquely by the statistics of a scene or subscene, and taking full account of any correlations that exist between different bands.

It should be remarked here that one general approach to this problem of band choice is through the use of principal component images (Taylor, 1974; Merembeck, 1977). In a statistical sense, the use of the first three principal component images in a color combination presents as much information as possible, using three colors. For a Landsat Multispectral Scanner (MSS) image, these first three components will often account for more than 99 percent of scene variance (Lillesand and Kiefer, 1979). However, use of principal components introduces a new problem. The colors of features in the combined image are completely data dependent, and it is therefore difficult for an interpreter to apply any previous experience of color-surface relationships to the analysis of a principal components image. The final potential of principal component images is still largely unexplored, and an alternative approach is now presented.

Definition of the Method

Consider the 7 by 7 variance-covariance matrix, **M**, for a scene or subscene (ignoring for the moment the fact that the TM thermal band is of inherently lower resolution than the rest). Any triplet of bands will be represented within this 7 by 7 matrix by a 3 by 3 submatrix.

Considering now the three-dimensional subspace spanned by any particular band triplet, the associated variance-covariance matrix defines an ellipsoid within the subspace. Further, the sum of the squared principal axes of this ellipsoid represents the total variance accounted for by these three bands (see Figure 1). One could plausibly (but as we shall see, wrongly) argue that the best three bands are those with the largest sum of squared principal axes, which hence account for the largest total variance. This is, after all, exactly the argument applied in employing principal component images. Because the trace of a matrix is invariant under rotational transformations, and because the sum of

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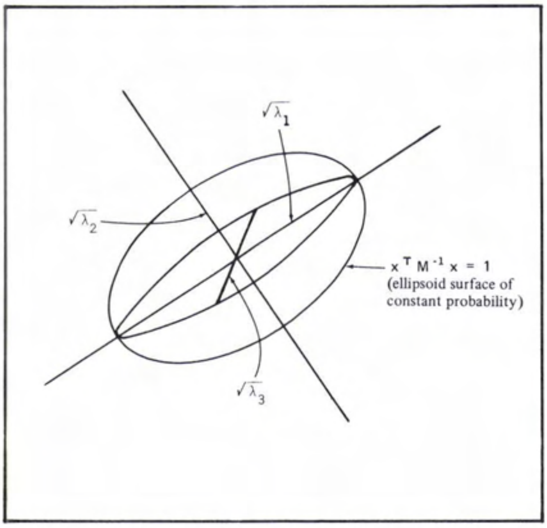

FIG. 1. The variance-covariance ellipsoid, principal axes $\sqrt{\lambda_1}$, $\sqrt{\lambda_2}$, $\sqrt{\lambda_3}$.

squared principal axes is equal to that trace, the band triplet that accounts for the most possible variance can be found from the original variance-covariance matrix simply by selecting the three bands with the largest diagonal elements. There is no need to examine all 35 band combinations.

To see what is wrong with this approach, consider an extreme case where there happens to be perfect correlation between a pair of bands. For convenience, suppose that those bands are 1 and 2, and suppose that the variance of band 1 (and therefore of 2) is larger than that of any other band. The 7 by 7 matrix **M** then has the form

$$\begin{bmatrix} a & a & \cdot & \cdot & \cdot & \cdot & \cdot \\ a & a & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & b & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & c & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \end{bmatrix} \tag{1}$$

where $a > b, c, \ldots$

The rotation matrix that will diagonalize the upper left 2 by 2 submatrix then has the form

$$\begin{bmatrix} 1/\sqrt{2} & -1/\sqrt{2} & 0 & 0 & 0 & \cdots \\ 1/\sqrt{2} & 1/\sqrt{2} & 0 & 0 & 0 & \cdots \\ 0 & 0 & & & & \\ 0 & 0 & & & \mathbf{I} & \\ \cdot & \cdot & & & & \\ \cdot & \cdot & & & & \end{bmatrix} \tag{2}$$

and, thus, *after* rotation the upper left 2 by 2 submatrix will have the form

$$\begin{bmatrix} 2a & 0 & \\ 0 & 0 & \cdot \end{bmatrix} \tag{3}$$

As expected, one eigenvalue is zero; but the other is the sum of the variances from the original bands 1 and 2. Because a is assumed to be large, both bands 1 and 2 will be included in the triplet that accounts for maximum variance—despite the fact that if either one of them is used, adding the other contributes no new information.

The problem lies in the use of *total variance* as the measure for the information content of the band triplets. This is equivalent to use of the sum of squares of ellipsoid principal axes, and there is no penalty associated with a very small principal axis provided that it occurs in association with a large axis (see Figures 2 and 3), as was the case for the above example.

We propose the use of a different measure for the information content of the triplet, and one that avoids the undesirable property demonstrated above. We will select the ellipsoid of *maximum volume*. This discourages selection of pairs of bands with high correlation, because in such cases one eigenvalue will be close to zero and the corresponding ellipsoid volume will be small.

Because the ellipsoid volume is $4\pi abc/3$, where a, b, and c are the principal axes of the ellipsoid, the volume of the ellipsoid associated with a particular band triplet is a constant multiple of the square root of the product of the eigenvalues for the 3 by 3 variance-covariance matrix of that triplet. However, under rotational transformation the product of the eigenvalues is equal to the determinant of the

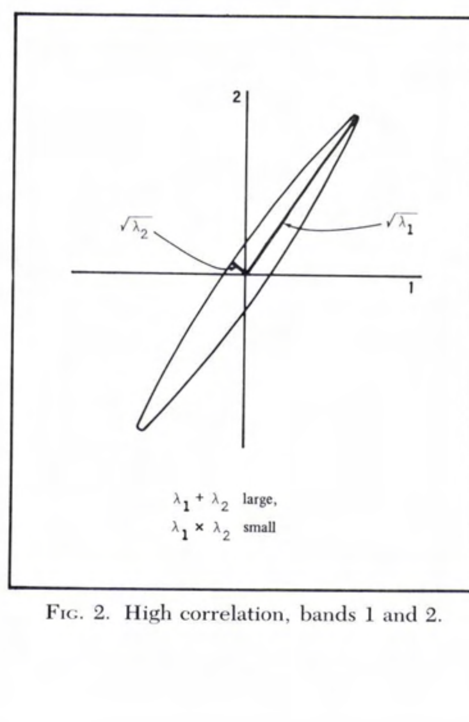

FIG. 2. High correlation, bands 1 and 2.

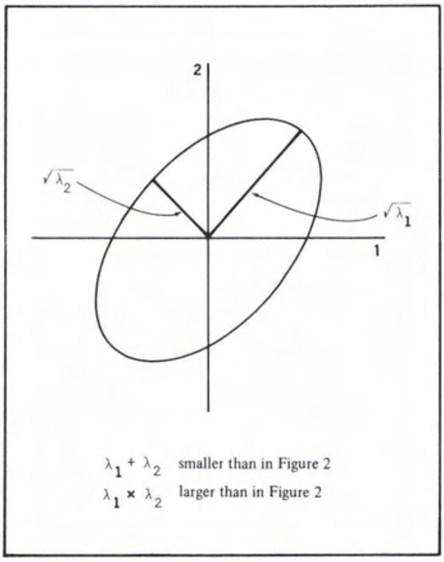

FIG. 3. Low correlation, bands 1 and 2, but lower individual variances.

original 3 by 3 submatrix. Thus, we can select the band triplet that provides the ellipsoid of maximum volume simply by computing and ranking in order the determinants of each 3 by 3 principal submatrix of the original matrix **M**. The band triplets associated with these determinants will then be ranked in order of decreasing overall information content. Given the original matrix **M**, the total computation to achieve this ranking is trivial. It requires a few hundred multiplications, followed by a sort of a list of 35 items. A BASIC program to perform this is given as an Appendix to this paper.

This procedure gives the best triplet, but the assignment of colors is still to be made. Now we can make use of the actual variances (the diagonal elements of **M**). Because the eye is most sensitive to green, next to red, and least to blue, we will assign green to the band triplet member of maximum variance (i.e., most variation within the image), red to the triplet member of second largest variance, and blue to the triplet member of smallest variance. The definition of bands for production of a color image is now complete.

THEORETICAL BASIS FOR THE SELECTION ALGORITHM

The procedure described in the last section seems reasonably logical and well-motivated, but in many cases it can be given further justification in terms of a standard image processing concept.

Suppose that the P bands of data can be described by a P-dimensional normal distribution, with probability density function given by Duda and Hart (1973): i.e.,

$$p(\mathbf{x}) = 1/K \ \exp[-(\mathbf{x} - \hat{\mathbf{x}})^{\mathrm{T}} \mathbf{M}^{-1} \ (\mathbf{x} - \hat{\mathbf{x}})/2] \qquad (4)$$

where $\hat{\mathbf{x}}$ is the mean of the distribution, **M** is the P by P variance-covariance matrix, and $K = (2\pi)^{P/2} |M|^{1/2}$ is the normalizing factor that gives unit probability when integrated over all space.

Then any N-band subset will similarly be described by an N-dimensional normal distribution of the form

$$p(\mathbf{z}) = 1/Ks \exp[-(\mathbf{z} - \hat{\mathbf{z}})^{\mathrm{T}} \mathbf{M}s^{-1} (\mathbf{z} - \hat{\mathbf{z}})/2] \qquad (5)$$

where $\hat{\mathbf{z}}$ is the mean of the subset distribution, $\mathbf{M}s$ is the corresponding N by N variance-covariance matrix, and Ks the appropriate normalizing factor that ensures unit value for the integrated probability.

The entropy of such an N-band subset of data is given by Hord (1982): i.e.,

$$S = -\int p(\mathbf{z}) \ln p(\mathbf{z}) \ d\mathbf{z} \qquad (6)$$
$$\text{all } N\text{-space, } V.$$

Thus, using Equation 5, and changing the origin of coordinates to the point $\hat{\mathbf{z}}$,

$$S = \ln(Ks) + 1/2 \int_V \mathbf{z}^{\mathrm{T}}\mathbf{M}s^{-1}\, \mathbf{z}\, p(\mathbf{z})\, d\mathbf{z} \qquad (7)$$

Thus,

$$2\,Ks\,[S - \ln(Ks)] = \int_V \mathbf{z}^{\mathrm{T}}\, \mathbf{M}s^{-1}\, \mathbf{z} \exp(-{}^1\!/\!_2\mathbf{z}^{\mathrm{T}}\, \mathbf{M}s^{-1}\, \mathbf{z})\, d\mathbf{z}. \qquad (8)$$

Rotating to principal axes, and noting that, because this is a pure rotation the Jacobian of the transformation is unity, the form $\mathbf{z}^{\mathrm{T}}\, \mathbf{M}s^{-1}\, \mathbf{z}$ becomes diagonal; thus,

$$\mathbf{z}^{\mathrm{T}}\, \mathbf{M}s^{-1}\, \mathbf{z} \rightarrow \sum_{i=1}^{N} (y_i^2/\sigma_i^2) \qquad (9)$$

where $\sigma_1, \sigma_2, \sigma_3, \ldots, \sigma_N$ are the square roots of the eigenvalues of $\mathbf{M}s$. (This matrix is positive semidefinite; thus, its eigenvalues are non-negative.) Thus,

$$2\,Ks\,[S - \ln(Ks)] = \int_{-\infty}^{\infty} y_1^2/\sigma_1^2 \exp(-y_1^2/2\sigma_1^2)dy_1 \int_{-\infty}^{\infty} \exp\left(-\sum_2^N y_i^2/2\sigma_i^2\right) dy_2 \ldots dy_N + (N-1) \text{ similar terms.} \qquad (10)$$

Using the integrals

$$\int_{-\infty}^{\infty} \exp\left(-y^2/2\sigma^2\right) dy = \sqrt{2\pi}\,\sigma \qquad (11)$$

and

$$\int_{-\infty}^{\infty} (y^2/\sigma^2) \exp\left(-y^2/2\sigma^2\right) dy = \sqrt{2\pi}\,\sigma, \qquad (12)$$

we then have

$$2\,Ks\,[S - \ln(Ks)] = N\,(2\pi)^{N/2}\,\sigma_1\sigma_2\sigma_3 \ldots \sigma_N = N\,(2\pi)^{N/2}\,|Ms|^{1/2}.$$

Because $Ks = (2\pi)^{N/2}\,|Ms|^{1/2}$, we have at once

$$S = N/2 + \ln(Ks) = N/2 + N/2\ln(2\pi) + 1/2\ln|Ms|. \qquad (13)$$

Apart from an additive constant, the entropy for the case of a normal distribution of data is thus half the logarithm of the determinant of the variance-covariance matrix. Choosing the N-band subset that maximizes this determinant is thus exactly equivalent to choosing the subset of N bands of maximum entropy.

Examples and Comments

For Thematic Mapper data, the procedure has been applied to a number of U.S. scenes of very different ground cover, including Washington, D.C., Death Valley, and Cement, Oklahoma. The results for Washington and for Death Valley are given in Tables 1 and 2, together with the associated variance-covariance matrices. The following comments apply to them, and to all other scenes studied to date:

(1) The band combination 1,4,5 (in the order blue, red, green) is usually, but not always, the selected triplet. In cases where it does not rank first, it usually ranks second. In the experiments conducted to date, the algorithm usually selects one band each from the visible, near infra-red, and short wave infra-red regions; and within those regions, bands of high individual variance are favored.

(2) Bands 1,4, and 5 of the original bands usually have a relatively high individual variance. These variances are decided, however, not only by the scene content, but also by the design of the Thematic Mapper (in an ideal instrument, all single band variances would *on average* be the same, so that each band on average occupies the same fraction of available grey levels; this is not true for the Thematic Mapper). Thus, the selection algorithm defines preferred band combinations for particular scenes *and sensors*. The bands favored for Thematic Mapper may not be those for another instrument, even for an instrument with identical spectral windows.

(3) The natural color combination 1,2,3 and the standard false color combination 2,3,4, both place far down in the rankings. In the case of the Washington, D.C. image, the natural color combination is 29th (lower than anything except some thermal band combinations, which are low for another reason to be discussed shortly); the 2,3,4 combination was ranked in 16th place. For Death Valley, the 1,2,3 natural color combination ranked 32nd, and the 2,3,4 combination just above it, at 31st. This is presumably a consequence of the very high correlations between the first four bands of the Death Valley scene.

(4) Triplets that rank high always include either band 5 or band 6 (note: the bands here are ordered by *increasing wavelength*, so the thermal band is band 7). This emphasizes the great importance of bands 5 and 6 on general information-bearing grounds.

(5) In independent experiments performed using many different band and color combinations of Thematic Mapper data, experienced interpreters unfamiliar with the analysis described here consistently ranked the 1,4,5 combination as one of their best choices (Colvocoresses, 1983).

Other considerations and comments

(1) The statistical analysis performed here used Thematic Mapper fully corrected or P tapes (which were readily available) in which the original histograms had already been modified by the gains and offsets. It would be preferable to work with data that have had no gains or offsets applied, i.e., with A tapes prior to any radiometric correction. If band

Table 1a. Variance-Covariance Matrix for the Washington, D.C. Scene, with Reduced Variance on the Thermal Channel

Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7*
53.32	27.41	35.74	5.86	36.04	33.56	7.77
27.41	17.01	21.35	11.36	29.35	21.29	4.13
35.74	21.35	31.66	20.01	46.46	31.03	6.69
5.86	11.36	20.01	131.71	131.64	38.14	8.26
36.04	29.35	46.56	131.64	210.83	86.25	19.10
33.56	21.29	31.03	38.14	86.25	50.01	11.51
7.77	4.13	6.69	8.26	19.10	11.51	9.80

* Thermal band is Band 7.

TABLE 1B. RANKED RESULTS FOR WASHINGTON, D.C. SCENE, WITH REDUCED THERMAL VARIANCE

Rank	Determinant	Band Combination*
1	433858	1, 4, 5
2	205811	3, 4, 5
3	138551	1, 4, 6
4	124784	2, 4, 5
5	101638	4, 5, 6
6	71723	1, 5, 6
7	62960	3, 4, 6
8	49759	1, 3, 5
9	39992	1, 3, 4
10	39609	2, 4, 6
11	36060	3, 5, 6
12	22847	1, 2, 5
13	21953	2, 5, 6
14	16732	1, 2, 4
15	11646	2, 3, 5
16	9709	2, 3, 4
17	7967	1, 3, 6
18	5094	4, 5, 7
19	4752	1, 5, 7
20	3634	1, 2, 6
21	3606	1, 4, 7
22	2294	4, 6, 7
23	2194	3, 5, 7
24	1945	3, 4, 7
25	1616	2, 3, 6
26	1386	5, 6, 7
27	1348	2, 5, 7
28	1130	2, 4, 7
29	727	1, 2, 3
30	688	1, 6, 7
31	276	3, 6, 7
32	215	1, 3, 7
33	175	2, 6, 7
34	84	1, 2, 7
35	43	2, 3, 7

* Thermal channel is Band 7.

selection of this type becomes common, it would be desirable to have such A tapes available as standard products.

(2) The thermal band is of lower resolution than the rest; thus, it would not be appropriate to give it the same weight in the selection process. How should one therefore deweight it? There is no clear answer to this question, but one could argue as follows: The maximum information that a scene can contain is given by the number of pixels, because in the limiting case, where there is no correlation between pixels, each would carry independent information about some feature of the surface. In such a case, the amount of information that the thermal band can contribute is only 1/16th that of the other bands, because there are 16 times fewer pixels. Therefore, one should deweight the thermal channel by a factor of 16. Such deweighting was performed in the experiments reported here. However, we should also note that this made no difference at all to the preferred band triplets, because even without deweighting we found no case where a triplet involving the thermal channel was in the top five. In practice, scene autocorrelation should certainly modify the weight factors (Labovitz and Masuoka, 1984).

(3) It is obvious when one looks at images created from the triplet 1,4,5 that for some applications this combination will be inferior to others, such as natural color and standard false color; for example, bridges are more easily seen on the 1,2,3 natural color combination. This restates the old truth, that one man's noise is another man's signal. However, the preferred triplets do tend to provide images of unusual clarity, with less residual striping than is seen in, for example, the natural color images. This is because the selection algorithm favors bands of high variance where strong contrast stretching is not necessary, and where the small grey level differences of residual striping are thus not amplified during image enhancement operations.

(4) Combinations such as 1,4,5 produce images with colors that are at first sight unfamiliar and unusual, but the assigned colors are not scene-dependent. Thus, in contrast to the scene-dependent colors of principal component or ratio images, the interpreter quickly learns to associate colors with particular ground condition. We therefore believe that there are definite advantages to seeking color composites of the original individual bands, rather than through band ratios or other band combinations.

(5) The approach developed here applies equally well to the problem of determining the best N bands from M original bands, regardless of the size of N

TABLE 2A. VARIANCE-COVARIANCE MATRIX FOR THE DEATH VALLEY SCENE, WITH REDUCED VARIANCE ON THE THERMAL CHANNEL

Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7*
251.64	146.31	198.55	176.41	246.36	144.63	5.30
146.31	90.40	125.40	112.95	178.63	105.16	10.33
198.55	125.0	181.12	163.27	276.44	162.93	22.50
176.41	112.95	163.27	159.70	262.74	152.99	14.79
246.36	178.63	276.44	262.74	627.47	366.90	75.38
144.63	105.16	162.93	152.99	366.90	223.38	48.73
5.30	10.33	22.50	14.79	75.38	48.73	69.89

* Thermal band is Band 7.

TABLE 2B. RANKED RESULTS FOR DEATH VALLEY SCENE, WITH REDUCED THERMAL VARIANCE

Rank	Determinant	Band Combination*
1	1462581	1, 4, 5
2	859695	1, 5, 6
3	684248	1, 3, 5
4	601687	1, 4, 6
5	432952	3, 4, 5
6	346425	1, 5, 7
7	328331	3, 5, 6
8	319827	2, 4, 5
9	275534	4, 5, 6
10	263989	1, 3, 6
11	219239	2, 5, 6
12	204146	1, 2, 5
13	167450	3, 4, 6
14	137060	3, 5, 7
15	127643	2, 4, 6
16	121117	1, 6, 7
17	107494	4, 5, 7
18	103781	2, 3, 5
19	89506	2, 5, 7
20	76827	1, 2, 6
21	75913	1, 3, 4
22	49163	3, 6, 7
23	40621	4, 6, 7
24	39230	2, 3, 6
25	37614	1, 4, 7
26	31621	2, 6, 7
27	21579	1, 3, 7
28	21322	1, 2, 4
29	20256	5, 6, 7
30	9168	3, 4, 7
31	8118	2, 3, 4
32	7895	1, 2, 3
33	7197	2, 4, 7
34	5037	1, 2, 7
35	2407	2, 3, 7

* Thermal channel is Band 7.

and M. Thus, the algorithm should be very useful in dealing with airborne scanner data, where the number of original channels is often large.

SUMMARY

The analysis given here provides a simple technique for selecting a small set of bands from N bands of data, where N may be large. The results obtained for Thematic Mapper data are interesting and revealing, because they select certain preferred three-band sets in a way that appears almost scene-independent. In particular, the 1,4,5 band combination consistently ranks high, regardless of image location. However, it should be emphasized that the only image data studied so far with this method have been those from the Thematic Mapper. Thus, sensor and scene characteristics cannot be decoupled. A similar analysis, for multispectral data from other instruments, might be revealing. It might allow band selection due to a particular *sensor* to be separated from band selection due to the fundamental reflective and emissive properties of the Earth's surface.

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APPENDIX
THE BEST-BAND PROGRAM

```
20 PRINT "SELECTION OF BEST THREE BANDS BASED ON ELLIPSOID VOLUME"
30 PRINT "DEATH VALLEY WITH REDUCED THERMAL VARIANCE"
40 DIM R(36),Q(36)
```

```
50  DIM U(36),V(36)
60  DIM M(8,8)
70  REMARK: M is the variance-covariance matrix for the scene or subscene.
80  REMARK: The arrays R,Q,U and V are storage arrays used in the program.
90  REMARK: Note that the program assumes that band 7 is the thermal data, and band 6 is the 2.2
    micrometre data.
100 REMARK: The instructions 190 to 230 (except for 220, which sets a count) reduce the variance
    of the thermal channel to allow for the lower spatial resolution of the thermal channel pixel.
190  FOR I = 1 TO 6
200 M(I,7) = M(I,7) / 4
210  NEXT
220 C = 1
230 M(7,7) = M(7,7) / 16
240  PRINT "RANK     DETERMINANT     COMBINATION"
250  FOR I = 1 TO 5
260  FOR J = I + 1 TO 6
270  FOR K = J + 1 TO 7
280 D1 = M(I,I) * (M(J,J) * M(K,K) - M(J,K) ↑ 2)
290 D2 = M(I,J) * (M(J,K) * M(I,K) - M(I,J) * M(K,K))
300 D3 = M(I,K) * (M(I,J) * M(J,K) - M(I,K) * M(J,J))
310 DT = D1 + D2 + D3
315 REMARK: The next instruction makes the determinant an integer; this is not necessary, it is done
    for convenience of output only.
320 DT = INT (DT)
330 N = 100 * I + 10 * J + K
340 R(C) = DT:Q(C) = N
350 C = C + 1
360 NEXT
370 NEXT
380 NEXT
385 REMARK: The next piece of code sorts the determinant into descending order.
390  FOR I = 1 TO 35
400 N = 0
410  FOR J = 1 TO 35
420  IF R(I) < R(J) THEN 440
430 N = N + 1
440  NEXT
450 U(N) = R(I):V(N) = Q(I)
460  NEXT
470  FOR I = 1 TO 35
480  PRINT I,U(I),V(I)
490  NEXT
510  END
```

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