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MATCHING OF PLANT VARIETY IMAGES FROM DIFFERENT SOWINGS

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MATCHING OF PLANT VARIETY IMAGES FROM DIFFERENT SOWINGS

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SUMMARY

Digital photographs of plants are increasingly used in variety registration trials to measure individual features. In this paper, an approach is described for summarising a composite of these features with the aim of automating the matching of variety images. A combination of statistical techniques is used to extract the main characteristics contained in a digitised image of a plant. The information is then used to search for varieties with similar features in an image database. The operation of the system with four seasons of data from carrot (*Daucus carota L.*) trials is described, with particular focus on the problem of matching images from different sowings.

INTRODUCTION

Digital photographs of plants have long been considered for use in variety registration trials to measure individual attributes of crop varieties (e.g. Keefe & Draper 1988, van de Vooren & van der Heijden 1993, McMichael & Camlin 1994). Image analysis offers a means to measure UPOV-defined characters efficiently, precisely and objectively, particularly for some characters that are difficult to measure otherwise.

In Davey *et al* 1997, Horgan 2001, Horgan *et al* 2001, the idea of encompassing composite features of an image of a plant part with a view to matching images was introduced. Such composite features might include the shape of the plant part or the colour distribution and pattern within the object.

Matching images of plant varieties could be used to identify a set of close controls from the reference collection for a candidate variety. This could be used to aid the planning of DUS experiments. For this to be useful, it is necessary to show that images of plant varieties from different years of trials can be successfully matched.

In this paper, we demonstrate the potential of image analysis to make meaningful comparisons between plant varieties even when images are taken from different sowings. To illustrate the techniques, we extract information relating to shape and colour distribution from images of sliced carrot roots. We then apply multivariate statistical techniques to compare and match varieties.

IMAGES AND FEATURE EXTRACTION

Photographs of carrot roots have been taken during 4 years of DUS trials at the UK Vegetable DUS centre at the Scottish Agricultural Science Agency in Edinburgh. 53 varieties are represented, most of which have images from more than one year. For each variety in each year, a photograph was taken of sliced roots from each of two replicates. There were 4 to 6 roots in each image. A typical photograph is shown in Figure 1. Image size was typically 250 to 500 pixels on each side.

Figure 1. Photograph of sliced carrot roots obtained from a plot of a single variety

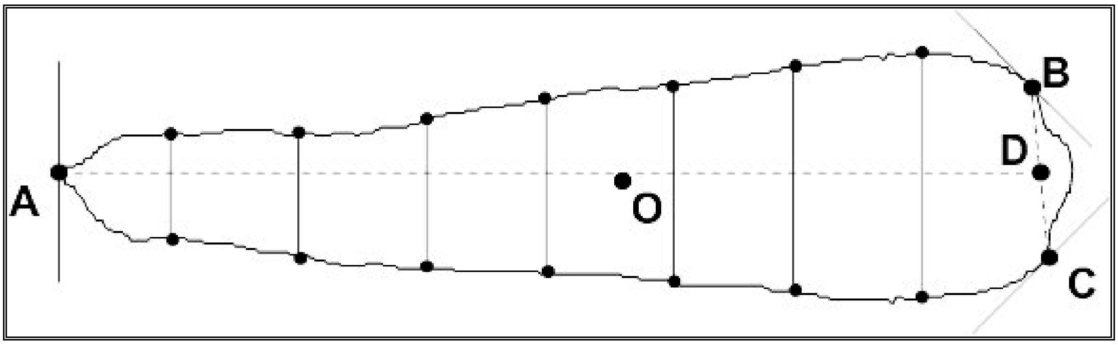
In this section, we describe how colour and shape information was extracted from carrot images**.** Horgan 2001 describes more generally how such information can be extracted from plant images, and Davey *et al* 1997 and Horgan *et al* 2001 describe the carrot example in more detail.

Shape

We adopted a widely used approach to study the variation in the shape of the sliced carrot roots**.** Landmark points (Dyden & Mardia 1998) were defined around the outline of the roots**.** The 17 landmark points chosen were at the tip of the carrot (A), the top and bottom shoulders of the crown (B and C), and the top and bottom edges for each of 7 equally spaced positions between the tip and the midpoint of the crown shoulders**.** The positions of the landmark points are illustrated in Figure 2.

For each carrot, 17 pairs of (x, y) co-ordinates corresponding to the landmark points were extracted automatically**.** Principal components analysis (Krzanowski 2000) can be used to study such multivariate variation between objects**.** We carried out principal components analysis on the covariance matrix for the 312 carrots from 26 varieties that were tested in 1995**.** The loadings derived from these components were then used to create principal components scores for the landmark data from the images of all 4 years**.**

Figure 2. Outline of a carrot root showing landmark points



The first 6 components accounted for 72%, 11%, 8%, 3%, 2% and 1% of the total variability respectively. The first component accounted for a large proportion of the variation and represented variation from long, thin carrots to short, thick carrots. The second component showed the degree of tapering present in the carrots, varying from a cylindrical form to a conical form. The third component represented the thickness of the carrot. The fourth and fifth components seemed to correspond to the degree of bending and asymmetry over the length of the carrot respectively. Since these two components were dependent on the orientation of the carrot, we used their absolute values. The sixth component seemed to relate to the degree of tapering in the tip of the carrots.

Colour

An initial study of the carrot images found that the most relevant variation in colour was in the green component. Therefore the colour images were converted to monochrome images based on the intensity of the green component. This simplified subsequent computations. The outlines of the roots were then warped to a common shape (Horgan 2001) to allow straightforward comparison of the colour distribution of the carrots on the same basis. Each of these processed images consisted of 27,000 pixels. The green intensity could be compared between carrots for corresponding pixels.

Comparison for all the pixels together is a high-dimensional multivariate problem. Principal components analysis (Krzanowski 2000) is a standard statistical procedure for enabling interpretation of this type of data and for reducing the data set to a more manageable size. The application of principal components analysis in this context (i.e. to warped grey-scale images) has been termed “eigenimage analysis”.

Principal component analysis was applied to the covariance matrix for a subset of 156 images representing the 26 varieties tested in 1995. Loadings from the first 5 principal or eigenimage components were chosen to create eigenimage scores for the images of all 4 years. These components accounted for 31%, 10%, 8%, 3% and 2% of the total variability respectively. Tentative interpretations of these components were made: the first component showed variability in the core to cortex contrast; the second component showed variability in the thickness of the core; the third component showed variability in the level of tapering of the core; the fourth component showed variability in the brightness at the core-cortex boundary; the fifth component showed variability in the contrast within the core between the tip and crown.

MATCHING & COMPARISON OF VARIETIES

The previous section showed how shape and colour scores have been obtained from the carrot root images. A data set has been produced consisting of 6 shape principal components and 5 colour components for 1684 sliced carrot roots from 53 varieties from 4 years of trials.

In this section, we look at how varieties may be compared and matched using the information extracted from the images as described above. Different classification methods are discussed and applied to the carrot data set. We look particularly at the problems associated with differences in experimental conditions between years.

Relationships between shape and colour components

Since the carrot roots were warped to a common shape, no relationship between shape and colour components would be expected. Table 1 shows the correlations between shape and colour components based on all 1684 images. There were small correlations between the first shape and colour components and between the second shape and colour components. However the table indicates that shape and colour scores carried independent information.

Table 1. Correlations between shape and colour components

	Shape1	**Shape2**	**Shape3**	**Shape4**	**Shape5**	**Shape6**
Colour1	0.25	0.07	-0.07	-0.09	-0.07	-0.07
Colour2	-0.01	-0.48	-0.24	0.05	0.09	0.18
Colour3	-0.06	0.00	-0.18	-0.03	-0.02	0.12
Colour4	0.06	-0.12	-0.02	-0.09	-0.08	0.00
Colour5	-0.29	0.26	-0.04	0.13	0.05	0.05

Presence of varieties over years

Differences in the image scores of a variety may be expected to exist between years due to varying experimental and photographic conditions. With such differences between years, appropriate adjustments to the image scores may improve comparisons between varieties.

The carrots were sampled from DUS trials and, as a result, varieties were not necessarily represented every year. In fact, only 2 varieties were represented in all 4 years, 11 varieties were represented in 3 years, 7 varieties in 2 years and more than half the varieties, 28, were represented only once. Table 2 shows how many varieties were in common between pairs of years as well as the number of varieties sampled in each year.

Table 2. Numbers of carrot varieties represented in each year and in common between pairs of years

	1995	**1996**	**1997**	**1998**
1995	**26**			
1996	4	**25**		
1997	11	17	**30**	
1998	4	9	12	**24**

Adjustments for year effects

A number of methods were considered for adjusting the landmark and eigenimage scores for year effects. Some were univariate, with adjustments being made to each component individually, and one was multivariate and adjustments were made for all components together. The methods are listed below, in increasing order of complexity:

a) No adjustment.

   The scores were used directly without adjustment.

b) Scores adjusted by year mean.

   The scores are adjusted individually by subtracting the relevant year means. For the carrots, the year means needed to be calculated using a method that compensates for the fact that different varieties were represented each year. We used REML (Genstat 5 Committee 1993) to calculate the average scores for each year adjusted by variety.

c) Regression on 1997 results.

   1997 was chosen as a base year since it was the year with which other years had most varieties in common. Then the scores for each component for a particular year were transformed using the slope and intercept from a linear regression of the scores for the base year on that year. The regression was performed using mean scores for each variety, but applied the resulting linear transformation to the scores for individual carrot images. No transformation was applied when the regression was not significant at the 5% level.

d) Procrustes rotation.

   Procrustes rotation (Krzanowski 2000) is a multivariate procedure that allows one configuration of points in multidimensional space to be rotated and scaled so that the configuration matches as closely as possible to another corresponding configuration of points. For the carrots example, configurations were defined so that the dimensions or axes corresponded to the eleven components, and the scores of each image defined a point in the configuration. Each year defined a separate configuration. 1997 was again chosen as a base year with a view to transforming the other three years to be more similar to the configuration for 1997. In practice, scores were first adjusted by the year mean as for (b) above, then each of the configurations for 1995, 1996 and 1998 were compared with the configuration for 1997 using mean scores for varieties in common between the two years. This yielded rotation matrices and scaling parameters for each of the three comparisons, and these were then applied to the scores for each carrot.

The method of adjusting by means was found to be the best in practice for the carrots example. It gave the best success rates for the discrimination methods described in the next section.

Matching varieties

An important use of the image information will be to find the closest matching varieties in the reference collection. To do this, a distance measure must be defined between the candidate and each of the reference varieties. There are many different possible distance measures. The following were considered:

1. Nearest neighbour (Euclidean)

$$d_j^2 = \min_k \sum_i (x_i - r_{ijk})^2 = \min_k (\boldsymbol{x} - \boldsymbol{r_{jk}})^T (\boldsymbol{x} - \boldsymbol{r}_{jk})$$

where x_i is the i[th] component (of 11 shape and eigenimage components) for the image of the candidate and $\boldsymbol{x}$ is the corresponding 11-dimensional vector, r_{ijk} is the i[th] component of the k[th] image of the j[th] variety in the reference collection and $\boldsymbol{r}_{jk}$ is the corresponding vector of components.

2. Nearest neighbour (Mahalanobis)

$$d_j^2 = \min_k (\boldsymbol{x} - \boldsymbol{r_{jk}})^T \mathbf{S}^{-1} (\boldsymbol{x} - \boldsymbol{r}_{jk})$$

where $\mathbf{S}^{-1}$ is the inverse of the pooled within-variety covariance matrix for the reference collection.

3. Linear discriminant (Fisher)

$$d_j^2 = (\boldsymbol{x} - \boldsymbol{m_j})^T \mathbf{S}^{-1} (\boldsymbol{x} - \boldsymbol{m}_j)$$

where $\boldsymbol{m}_j$ is the mean vector for the images of the j[th] variety in the reference collection.

These measures all have similar forms and are examples of distance measures used in discriminant analysis (Hand 1981). They differ in whether the distance is measured to nearest of the individual images for a reference variety or to the mean of the images for a reference variety, and whether the distance is scaled by the pooled within-variety covariance matrix. Using such a distance measure, it is then possible to calculate which of the reference varieties is the nearest to the candidate.

These measures were tested on the carrot sliced root image data using cross-validation (Hand 1981). The images from each year in turn played the part of candidates and were matched against the images of varieties from the other three years. The success of a method was judged by the number of times that a “candidate” variety image was matched to the same variety in the “reference set”. This cross-validation scheme should give an unbiased estimate of the success rate and simulates the real-life situation of matching images of new varieties with images of existing varieties. Only candidate varieties that were also present in the reference set were included in the assessment of success.

For the two nearest neighbour distances, scores for both the candidate and reference set were averaged within plots. For the linear discriminant distance, the candidates were based on within-plot means, but all the individual images were used to form the reference set. The scores for each component were adjusted for year effects as described above.

The success-rates were compared between the different methods of adjusting for years, between the three distance measures and between different combinations of the shape and eigenimage components. Table 3 shows the success-rates obtained using the nearest neighbour (Mahalanobis) and linear discriminant distances for the four different adjustment methods using all shape and colour components. The results for the nearest neighbour

(Euclidean) distance are not shown since it did not seem sensible to use a combination of components on different measurement scales for this metric.

Table 3. Cross-validated (by year) success-rates for different adjustment and matching methods using all components.

Year adjustment method	Matching Method: Nearest neighbour (Mahalanobis)	Linear discriminant
None	30%	37%
Mean	39%	48%
Regression on 1997	37%	41%
Procrustes	19%	27%

Table 4 compares the success-rates obtained between the three distance measures on different combinations of components (shape components, eigenimage components, and all components). In this case, the scores were adjusted by the year mean.

Table 4. Cross-validated (by year) success-rates for different combinations of components and matching methods using the mean year adjustment method

Combination of components	Matching Method: Nearest neighbour (Euclidean)	Nearest neighbour (Mahalanobis)	Linear discriminant
Shape only	23%	31%	27%
Colour only	12%	22%	19%
All components	N/A	39%	48%

It was concluded from these results that, for the carrot data, the most effective method for adjusting for year effects was to subtract adjusted-year means, that it was more effective to use all the shape and colour components combined than either shape or colour components alone, and that the linear discriminant proved to be the best distance measure of the three. The best success-rate achieved above was 48%, and additionally we found that for 82% of candidate images, the matching variety in the reference set was within the 5 nearest varieties.

One potential use of these techniques would be to indicate into which group within the reference collection a candidate variety should be allocated. Independently of this analysis, the 53 carrot varieties were allocated to 9 groups defined by DUS characters. Three varieties did not naturally fall into any of these groups and so were not considered further. The results for the cross-validated linear discriminant analysis with the adjusted-year mean method were reviewed in terms of seeing how well groups were matched. It was found that 78% of candidate images were matched into their appropriate group.

DISCUSSION

This paper has shown how composite features extracted from images of carrot roots can be successfully used to match two images of a variety even when images derive from different sowings. It was possible to identify the correct morphological group for a candidate variety with around 80% success, based on a bank of images of varieties from previous years' trials. This seems impressive as the images of sliced roots represent only one aspect of the morphology of carrots used to define varieties and groupings of varieties. In general, the images might be used in combination with other information to improve the accuracy of matching.

Matching of images in this way has potential to assist the planning of DUS trials by identification for candidate varieties of close controls from the reference collection. It could also prove useful for studying variety relationships within reference collections.

At the Scottish Agricultural Science Agency, there is an on-going project to enable the routine measurement of UPOV characters for vegetable varieties using digital images. Digital images of plants parts produced for measurement of DUS characters could also be used to build an image database. Such a database could be used as basis for matching varieties as described in this report. A prototype for such a system is described in TWC 16/10 and demonstrated on the Internet at www.bioss.ac.uk/visor/.

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