CORRESPONDENCE ANALYSIS APPLIED TO IMAGE MATCHING AND MAP UPDATING

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ABSTRACT:

Correspondence analysis or similarity detection is a central thema in our R&D on "stereo" image matching, texture analysis pattern analysis and map updating. We propose a common method replacing classical autocorrelation and cross correlation.A central thema is the use of "distance" in feature space used as a similarity criterion. Several practical applications are refered to. The search space for corresponding objects is limited by the application of knowledge and models.

INTRODUCTION

In our R&D on methods of information extraction from R.S. data and integration with old information stored in databases or maps there is a need for unifying principles. Present R&D fields involve image segmentation, object detection and classification, extraction of pattern and texture descriptors, DEM generation from multiple view imagery and computer assisted map updating.

Common to these fields are principles of feature extraction and pattern recognition including structural pattern recognition which puts emphasis of the detection of structure primitives and the relation between primitives. Feature extraction and classification occur at various levels of abstraction. The lowest levels are formed by signal processing methods such as matching by correlation, the application of linear filters and operators. At the higher levels we are concerned with objects with their related attribute lists and their topological relations as stored in the region adjacency graph. On top of this level explicit distance relations may be required. For the link with database (GIS) environments there is a need to put

the object relations in a data base format which is compatible with popular (coordinate oriented) databases. As an example ,a link was made between our Context Vision GOP and ARC-INFO.
The main emphasis in this paper is to explore the common ground between various applications of correspondence analysis.

CORRESPONDENCE ANALYSES & PATTERN RECOGNITION

Pattern Recognition aims at the classification of objects on the bases of their features. Features are represented as feature vectors in the case of ordinal data and as attribute lists in the case of nominal data, the property list is a mixed form of data types. The cognition phase in PR assumes knowing or learning. Learning or training can be supervised or unsupervised.
Correspondence analyses is a special case of Pattern Recognition where for each object in the scene (or map) a comparison is made with neighbouring objects in the same image (selfsimilarity) or in an other image (map), (cross similarity). Both in pattern recognition and in correspondence analysis features have to be defined and a metric in feature space has to be choosen which can serve as a measure for similarity.

FEATURE EXTRACTION / SELECTION

Features are measurements, transformed measurements or attributes of objects which allow maximum separation between different classes of objects using a minimum data volume.

Feature extraction should be based on knowledge but in practice it is often based on statistics or tricks from classical signal processing.

Spectral features are derived from multi spectral channel data. The numerical data represent reflected radiation as measured by sensors based on photon counting. Knowledge from modelling the interaction of photons with matter is used to map the data from the domain of photon reflection into the domain of applications e.i. mapping 6 channel TM data into a green vegetation index and total reflected photon flux ("panchromatic").

Spatial features are characteristic data containing information about spatial relations such as size, shape, texture, adjacency, distance to ..

Temporal features are derived from characteristic changes in attributes of objects over time, such as the change of green vegetation index during a growing season.

SPATIAL FEATURES

Spatial features are mostly derived from a segmentation process. Segmentation by merging is choosen here instead of segmentation by edge detection because edge detection is based on differentiation which enhances the noise more than the signal and usually provides open boundaries of segments. Moment features are : area, centre of gravity, moments of inertia -> main axis of inertia. A shape feature is derived from area/boundary**2. Shape description is encoded in the boundary chain code (relative vectors). Topology is contained in the region adjacency graph. Node density can be used as a measure for bussiness. After the extraction of structure elements, the elements are symbolic spatial features themselves and they are related in a topological consistent way.

COMPATIBILITY WITH VECTOR DATA BASES.

In order to be able to access old data and to add new data to a vector data base environment the area covering objects and segments are once differentiated to provide relative boundary vectors, the second differentiation provides the nodes, attributes are passed via ASCII code.

A two way interface between our Context Vision GOP (pattern recognition machine) and ARC-INFO running on a VAX has been completed (March 1988)

FEATURE SPACE METRICS

The definition of proper feature space metrics is crucial for the scientific quality of R&D results. Too often a metric is implicitly choosen which does not make sense in terms of the physical dimension of the feature vectors.

ORDINAL FEATURES :

CORRELATION

Auto correlation and cross correlation are popular methods from signal processing for the quantification of self- and cross similarity. The feature vectors **V** and **W** are normalised by vector length to **v**, **w** and then smilarity is defined as

$$\cos(\text{angle}) = \mathbf{v}.\mathbf{w}$$

For data generated by optical sensors the components of **V** and **W** consist of photon counts. The vector length involves taking the square root of the sum of photons squared which clearly does not make sense. Also taking the cosine of an angle is a bad choise of similarity measure as with similar feature vectors angle -> 0 and cos(angle) = 1 - 1/2 (angle)**2.
As auto correlation and cross correlation suffer these disadvantages we have introduced the sum norm in those cases where the scene radiation model indicates the need to remove overall fluctuations which are not relevant to the correspondence analysis.

SUM NORM

The sum norm is defined as

$$\mathrm{v} = \frac{\mathbf{V}}{\mathbf{V}\ .\ \mathbf{N}} \quad \text{with} \quad \mathbf{N} = (1,1,..)/n \text{ , n components}$$

The physical interpretation of the sum is the sum of photons over the spectral channels and the sum norm represents the probability that a reflected (or emitted photon) would come from a certain feature vector component (spectral or spatial).
An artefact is produced when the sum norm is applied to a spatial feature vector defined by a moving window. The normalised image has the appearance of the result of a Laplace operator. The explanation of this can be found by considering that our eyes take the log of the incoming photon flux :

$$\log(\mathrm{v}) = \log(\mathbf{V}) - \log(\mathbf{V}\ .\ \mathbf{N})$$

As $\mathbf{U} - (\mathbf{U}\ .\ \mathbf{N})$ equals the Laplacian operator, the appearance of the artefact is explained.

A conclusion from the interpretation of this artefact is that one should be very carefull in applying further differentiation operators as all differentiation operators enhance isolated scene elements (noise) more than lines which in turn are more enhanced than edges in proportions 8 : 6 : 3 (3 x 3 Laplace operator).

The application of a vector norm produces similar artefacts. Normalisation should be avoided unless feature extraction absolutely requires it.

EUCLIDEAN DISTANCE:

An alternative to the correlation measure would seem to be Euclidean distance between a reference feature vector and the vector frrom the object under observation. The initial problem with this measure is the same as for vector length. The solution is to include the concept of likelyhood. The problem of correspondence analyses and similarity detection must be reformulated in terms of testing hypothesis of the kind "the object is similar" vs "the object is not similar" or "the object belongs to the same class" vs "the object belongs to a different class".

If the probability distribution of the vectors in featurespace is isotropic then the Euclidean distance in featurespace in directly related to the likelyhood of class membership (similar vs nonsimilar).

MAHANALOBIS DISTANCE

If the probability distributions are non-isotropic then the Mahanalobis distance can be used as a measure for (dis)similarity. In order to calculate it , the assumption of a unimodal multivariate distribution is often made. The covariance matrix for each class defines the local anisotropy in featurespace.

CITY BLOCK DISTANCE

If the features are independant and a study of featurespace clustering shows rectangular clusters then the cityblock distance would be the appropriate measures.

NOMINAL DATA

Nominal features are represented as attribute tupples or strings.

The relation between classification on nominal features (attributes) and ordinal features is illustrated by defining intervals on ordinal data and using an AND function.

If ordinal features are statistically independant then a box (parallellepiped) classifier is equivalent to a number of interval decision functions connected by AND functions. If the data show dependency then a combination of AND and OR functions should be used.

STRING "DISTANCE" = CITY BLOCK DISTANCE

In nominal feature space each cell is a unit box. The "distance between two equal leght attribute strings (Boolean) is then defined as the number of attributes which are not equal.

D_c ({a,b,p,q),(a,b,r,s}) = 2

COST OF SUBSTITUTION , FUZZY STRING MATCHING

Assume two strings of the same length R$ = "a , b , c , d" and X$ = "a , p , q , d" The distance between R$ and X$ is defined as the cost of "mending" string X$ into a copy of R$. Each position in the string has its own cost of replacement Ci. The cost of replacement in the example is C1 + C2. This method is generalisation of the cityblock distance.

If the cost of substitution depends also on the old value then the cost per position is retrieved from a cost matrix :

COST(ref.,old,new)

CHAINCODE MATCHING

A hybrid form of data is made up of strings of relative vectors encoded as a chaincode derived from the differentiation of one or more attributes of objects or segments (in the rasterdomain naturally). In matching corresponding shapes ,the chaincode strings should be ideally the same but in practice they are different and may have a different length . In deriving a distance measure for these boundary features the vector nature of the data must be taken into account. Instead of chain code substitution the distance can be calculated between the best fit of the list of coordinates from the one boundary relative to the reference boundary. The cost factor is in that case equivalent to the energy needed for elastic stretching of the raster.

APPLICATIONS of CORRESPONDENCE ANALYSIS

SELF SIMILARITY

TEXTURE ANALYSIS,

Segment an image by connecting nearest (spectrally)similar neighbours. Calculate a number of properties for each segment. Use the region adjacency graph for addressing the neighbour segments and their property lists. Either search the neighbourhood for the most similar segments (minimum distance in property space) or look at the statistics of differencing property strings over common boundaries. Thresholding will produce a network of connected similar segments which can be used for further segmentation.

PATTERN ANALYSIS,

Pattern is a special case of texture which is easier to model. For instance for large rectangular objects (flats, houses) find the nearest similar objects.
Constraints ; flats are supposed to be parallel, flats must cast large shadows parallel to the sun's direction (sun elevation and azimuth, two storey houses also cast a predictable shadow but their orientation can change.

CROSS SIMILARITY

The problem is to find similar objects in another image. In practice self similarity must be known first before judgement can be passed on cross similarity.

Example : old pan image, new pan. image, old map, find the corresponding objects in the old map / image pair, mark significant changes in the new image -> update map.
Constraints ; lines found in the old map limit the search for lines in the old image, changes in the new image must cover ares compatible with major new roads, changes in smaller roads are only looked for adjacent to major changes in large roads.

Example : a multiple view (stereo) image pair, resampled to epipolar lines, spatial features derived from reflection

profiles; maximum and minimum position and amplitude, first derivative (edge strength), record shift parameter at maximum similarity.
Constraints ; elevations found from one scanline limit the search along the next epipolar scan.

Example : multiple view (stereo) SPOT, resampled to almost epipolar lines, spectral feature = sumnormed X-channel 3 (Infrared), spatial features per segment ; segment size, centre of gravity cgx,cgy, shape factor (elongatedness), merge level, boundary chaincode, position of nodes nox,noy.
Constraints : maximum slope and hight differences constraints search space along epipolar lines(± tolerance), large segments put elevation constraints on smaller segments.

In the poster session the principle plus the examples will be illustrated using graphics and images from the ISPRS papers on mapupdating, DEM generation using SPOT, and texture analysis.

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