FEATURE SELECTION IN COLOUR IMAGES FOR TOKEN MATCHING

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ABSTRACT

We are currently developing an algorithm for knowledge-based correspondence analysis in dynamic stereo images. In this paper we describe the feature selection algorithms and the relational data structure used for matching. We also present a clustering algorithm that is used to group the tokens into sets of similar tokens. The matching algorithm uses this classification information to plan a matching strategy. The least ambiguous image features are matched first and are used as a 'handle' for constraint propagation. We present two algorithms for feature selection in colour images — a region grower and an interest operator, as well as experimental results for point classification and region classification.

I INTRODUCTION

We are currently implementing a knowledge-based vision system called SISSY (Stereo Image Sequences SYstem) for 3-D reconstruction from dynamic stereo images using a knowledge-based approach. The input are colour images, since colour provides additional features for matching and also for the classification of boundaries. The system consists of the following modules:

1. Modules to compute a rich *structurad image description* based on regions, edges, straight lines, vertices, critical points, texture, and optical flow fields **[Bartsch et al. 86]**.
2. *A classification module [Dreschler-Fiicher +Trlend184]* performing a clustering algorithm on the features and grouping ambiguous features (according to some similarity criteron) into equivalence classes. The correspondence analysis starts with matching classes of features rather than features. Classes with only few elements are matched first, since unique features may provide a starting point for constraint propagation.
3. A *matching module* for knowledge based correspondence analysis, implemented as a blackboard system with supervisor, scheduler, dispatcher, blackboard, attention list, and a procedural knowledge base for geometric and kinetic reasoning.
4. The *fuzzy temporal geometric scene description* reflecting the state of the geometrical reconstruction accomplished so for — object descriptions, observer motion, moving and stationary objects, light sources —■ together with information on numerical accuracy and confidence.

This paper describes the feature selection part of the SISSY-system; for a discussion of the correspondence analysis see *Dreschler-Fucher 86.*

II FEATURE SELECTION

A. Region Growing

There are two classical approaches to region growing — region growing via thresholding and region growing via merging *[Zucker 76],* Both approaches have advantages as well as drawbacks; region merging, generally, suffers from a lack of global knowledge, whereas thresholding is problematic because of neglecting the local context. Therefore, we suggest a region growing algorithm by hierarchical clustering in 5-D feature space, that combines position information with colour features. Each pixel is represented by a feature vector consisting of the three colour features ROB and the two image coordinates. Thus, pixels have to be similar in colour *and* in position to form a cluster in 5-D space. Since the clusters will be flat and of arbitrary shape, we chose a hierarchical clustering based on the minimal spanning tree (MST), which does neither require a functional model of the data, nor a fixed number of classes *[Zahn 11).* Graph-based clustering *reveals* structure in the data and does not *impose* structure, like model-based classification. This is important, since we do not want to use scene-specific knowledge.

Generally, the computation of the MST for a large data set is computationally expensive in storage and computation time requirements. These costs can be reduced considerably by the following observation: Typically, the nearest neighbor of a pixel in 5-D feature space is one of its 4-connected neighbors in the image. Therefore, we restrict the connections in the MST to those between 4-connected pixels.

A nice property of this clustering algorithm is that each subtree of the MST directly corresponds to a 4-connected subregion of the image. Thus, segmentation is done by simply removing inconsistent edges from the MST. The MST provides global as well as local information to detect such inconsistent edges. Since there is no restriction on sise and shape of the regions, the MST-algorithm can detect ebngated, thin regions as well as compact regions.

Burr + Chien 16 used a MST-algorithm region grower for black-and-white images and report similar good results. Burr and Chiens's algorithm divides the image into a set of elementary regions and fits planes to those regions. The MST is then constructed from these elementary regions. Contrary to Burr and Chien we compute the MST for single pixels, and thus achieve a finer spatial resolution. This is possible, because in colour images each pixel provides three intensity features, and thus we have a feature vector already on pixel level.

Fig. 1 shows the segmentation result for the house scene from fig. 2. The image was recorded on a sunny day. The sky is entirely deep blue and the houses are painted in pastell shades, the left one is light brown and the right one is pink. The image has a resolution of 192*256 pixels. Please, note that big compact regions are detected as well as small, ebngated regions.

B. Points of Interest

Points of interest are small local image features with significant variation of the image density function in more than one direction. Examples of points of interest are small dots, vertices, or endpoints of lines. Feature detectors for points of interest are usually called *interest operators.* Points of interest are important for 3-D reconstruction and correspondence analysis, since they provide well defined points for measurement. So far, interest operators have been developed only for black-and-white images.

Our main concern has been to verity the significance of colour information for feature detection and correspondence analysis. Therefore, we decided to use the interest operator of *Moravec 80* for first experiments with colour. Moravec's operator is easy to implement and we used this operator previously for motion analysis *[Dreschler + Nagel St].* We adapted Moravec's operator to colour images by changing the computation of the directional variances. Instead of computing squared grey value differences, the squared differences of colour vectors are computed.

Figure 2 shows the results obtained with the interest operator. Most of the visually interesting points are detected — see *Bartsch et al. 88* for a detailed discussion. These results have comfirmed our assumption that colour is a helpful cue for feature selection. At present we are developing an analytical interest operator for colour images, since analytical interest operators are superior to heuristic operators with respect to the spatial resolution.

C. Classification

After feature selection the features are grouped into similarity classes according to a similarity function. The classification module performs a clustering algorithm on the features using the same similarity function that is used by the correspondence algorithm. The correspondence analysis starts with matching classes of features rather than features. Classes with only few elements are matched first, since unique features may provide a starting point for constraint propagation.

The classification module uses a "minimal-spanning-tree"-algorithm for clustering, for the same reasons as the region grower. The minimal-spanning-tree is segmented by removing all edges longer than a threshold that is computed from the mean edge length and the variance of the edge length in the minimal spanning tree.

Classification of points — Fig. 2 shows classification results for the points of interest. The set of all points of interest is indicated by white markers. In each of the figures a and b one class of points is marked by black markers. Fig. 2a shows a class of "all points looking like the horisontal end points of cross-bars". Fig. 2b shows a class with only two members. There are some classes with points unique in the image and thus, a promising starting point for matching, e.g. the two top corners of the chimney. Please note that many points do look alike locally on pixel level, even when they are globally quite different in structure. The similarity function used for classification was the normalised cross-correlation in a 5-by-5 neighborhood.

Classification of regions — The classification of regions is based on a distance function computed from several features: area, mean RGB-values, compactness, and the principle moments of inertia. These features are scaled to sero mean and variance 1.0 to provide a uniform weight for all features.

Fig.3 shows results of the region classification. There is one big class of dark regions of more or less rectangular shape corresponding to the windows; A smaller class combines the five window regions that are darker than the others **(fig. 3b)**.

There are some classes with only one member, e.g. the sky region. Those unique regions may serve as starting points for the matching algorithm.

In addition to guiding the matching process we want to exploit the classification as second-order-features. For example, a class of points of interest with many members is a cue to textured regions; classes of parallel lines are helpful to detect separate objets.

III IMPLEMENTATION AND CONCLUSIONS

So far, we have implemented the modules for feature extraction from colour images that perform quite satisfactory (region growing, points of interest, edge detection) and a database for easy retrieval of structural image descriptions together with a versatile interactive graphical display facility *[Sprengel 86],* and there are promissing results for the classification of points of interest and regions. All algorithms presented here are programmed in Ada.

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Bartsch et al. 86 : *Merkmalsdetektion in Farbbildern als Grundlage zur Korrespondenzanalyse in Stereo-Bildfolgen,* Thomas Bartsch, Leonie S. Dreschler-Fischer, and Carsten Schroder, Proc. 8. DAGM-Symposium, Paderborn, West Germany , September 1986, G. Hartmann (Hrsg.), Informatik Fachbericht*e* 125, Springer Verlag Berlin Heidelberg New York Tokyo 1986, pp. 94-97.

Burr + Chien 76 : *The minimal spanning tree in visual data segmentation,* D.J. Burr and R.T. Chien, Proc. of the 3rd Int. Joint Conf. Pattern Recognition, Coronado, California, U.S.A., November 1976, pp. 519-523.

Dreschler + Nagel 82 : *Volumetric Model and 3D-Trajectory of a Moving Car Derived from Monocular TV Frame Sequences of a Street Scene,* L. Dreschler and H.-H. Nagel, *Computer Graphics* and Image *Processing* 20, 199-228 (1982).

Dreschler-Fischer 86 : *A Blackboard System for Dynamic Stereo Matching,* L.S. Dreschler-Fischer, Proc. 1st Int. Conf. on Autonomous Mobile Systems, Amsterdam, The Netherlands, December 1986, (in press) .

Dreschler-Fischer + Triendl 84 t *The ASTERIX-System: A Feature Based Approach to the Correspondence Problem,* Leonie S. Dreschler-Fischer and Ernst E. Triendl, Proc. DARPA-Image Understanding Workshop, New Orleans/La, October 1984, pp. 300-301.

Moravec 80 : *Obstacle Avoidance and Navigation in the Real World by a Seeing Robot Rover,* H.-P. Moravec, *Ph.D. Thesis* Dept. Comp. Science, Stanford University, Stanford/CA (1980)
see also:
Report CMU-RI-TR-3 Robotics Institute, Carnegie-Mellon-University, Pittsburgh/PA (September 1980) .

Sprengel 86 : *DESIRE - Entwurf einer Datenstruktur zur symbolischen Beschreibung von Bildern,* Rainer Sprengel, Technical *Note* FBI-HH-M142/86 Universitat Hamburg, Fachbereich Informatik, Hamburg, West Germany (November 1986).

Zahn 71 : *Graph-Theoretical Methods for Detecting and Describing Gestalt Clusters,* C.T. Zahn, IEEE Trans, on *Computers* C-20, 68-S6 (1971).

Zncker 76 : *Region Growing: Childhood and Adolescence,* S.W. Zucker, *Computer Graphics and* Image *Processing* 5, 382-399(1976).

Fig. 1: House scene: Segmentation results

2a) The class of window crossbars

2b) The class of gable points

2c) A unique point: Chimney top

Fig. 2: Classification results for Points of interest.

The points marked by black crosses belong to the same equivalence class.

3a) A class of small (not perfectly) rectangular regions

3b) A class of darker, rectangular regions

Fig. 3: Classification results for regions
The regions marked by black or white contours are members of the same equivalence class.