ANALTSIS OF THREE-DIMENSIUNAL SCENE DAGES ON THE KNOWLEDGE 07 THEIR TEXTURE FEATURES

M.G.Yegi,N,V.Zavaaishin,K.L.Sheinin
Institute of Control Sciences,Mo8Cow,USSR

Abstract

The paper describes an algorithm for identification of areas of uniform texture in a naif-tone image of a three-dimensional scene.

Introduction

In recent papers on analysis of three-dimensional scenes the initial half-tone image is regarded as texture(see e.g.1,2), This is attributable to the fact that the objects which the robot is to manipulate may look like "spatial texture",(e.g. threadxngs on a holt or nut,an assembly with a large number of identical parts). Also with the resolution of the perceptIn unit sufficiently high,tne micro-pattern or roughness of the material of which the are made may be mapped onto the image .The properties of the image texture depend on the object surfaces orientation relative to the perceptor axis of vision as well as on the material and the "spatial texture". Therefore different surfaces of the object are associated with more or less uniform areas with different structural properties in the image.

This paper will cover experimental study of the algorithm for identification of areas of uniform texture in a half-tone image of a three-dimensional scene.One specific feature of the study is that the initial material of the experiments were images of real objects that were prepared by an "eye-computer"system.Another was that theiarea identification algorithm uses analysis of integral texture characteristics on large areas of image.The image is first divided into fragments each treated as a separate texture then each fragment associated with a vector, which is a set of texture integral characteristics.Automatic classification algorithm divide the entire set of vectors into classes.As a result each fragment of the image ie associated with the score of the class or the texture type index* A totality of neighboring fragments with the same indices is regarded as an area of the same texture.

The paper consists of two sectios.The first will describe the integral texture characteristics used and the procedure for area identification.The second is devoted to description of experiments, confirming the validity of the method.

The experiments were conducted in collaboration with G.G.Valnshtein using an "eye-computer"system developed in the laborattory of D.S.Lebedev in the Institute of Inf ormationTransmission Problems Academy of Sciense USSR.The system is described in (5).

Area identification algorithms

Integral texture characteristics

Intuitively a texture image can be described in terms of the size and orientation of the grain.These features ,however,have a sense only for binary images where one can identify "repeating"elements of approximately similar shape,as done in (1).

We will propose a system of features intended for direct work with half-tone images.Following the above intuitive con cept of describing texture images the desired features should be such that give good assessment of grains and their period and direction of distribution in the textures to be analyzed.

A more straightforward definition of these features is obtained in using functions which describe the change of a certain measure of similarity between the image under study and the image obtaned from it by shifts depending on the step and direction of the shift .Indeed, the smaller,on the average,is the "repeating period"of the image in a certane direction, the stronger the decrease in similarity as a function of the shift.Consequently,the functions which describe the change of the similarity measure with a . shift in different directions carry sufficiently complete information on basic characteristics of half-tone images.

Assume that an analised image is specified on an MxN digital rastre•Consider a central M'xN' area which takes up almost the entire image .Coop are it with an area of similar site which is shifted with respect to the rastre center by a distance τ in direction φ .The similarity measure is a squared Eucledean distance between vectors of blackness distributions of associated images specified on M' x N' rastre.

The system of feasible shift directions will be specified as a system of four directions:rightwards,right and upwards, upwards, left and upwards.* Enumerate these directions as 1, 2, 3# 4. In each of these directions we will consider a set of different shifts V= 1, 2,..., n where n is small compared with min M'.N'.

• If necessary the number of shift directions can be easily increased* A crude four-direction system suffices, however, in many practical cases. Also, small shifts often give the same effect in simmetrical directions. This means that instead of two opposite directions only one can be studied.

Denote the blackening vector of the central area as x and that of the shifted area as x (τ,φ). The totality of values $R^2(x, x(\tau,\varphi))$– of squared Eucledean distances between the vector x and all vectors x (τ, φ) defined for $\varphi = 1,2,3,4$ and $\tau=1,\dots, n$ specifies a new vector x_R. This new vector is the desired vector of the mainapace of features.

Note that characteristics of the half-tone image essentially depend on the contrast. Therefore identical initial textures can be characterised by different vectors XR if they differ in the contrast. Therefore we propose that insted of using directly the vector x_R one should use the normalized vector 21 obtained by the formula

$$\tilde{x}_R = x_R/\sigma^2,$$

where σ^2 is tnevariance of blackness distribution for an image.

Area identification procedure.

The image of a three dimensional scene to be analyzed was obtained through an "eye-computer" system whose programs are described in (3) . This programs handle automatic focusing and image input into the digital computer.

By a special program all images were divided into a totality of equally spaced fragments. For each fragment the values of vector $\tilde{x}_R$ components were computed. The totality of these vectors was processed through one of the automatic classification algorithms described in (4) . The processing resulted in an image in which the center of each fragment was marked by the symbol of the class with which the fragment was identified.

Area identification experiments

Figure I shows photographs of objects on which experiments were staged. Each such object or a totality of objects were placed in front of an "eye - computer" TV camera. Following automatic focusing the initial scene was introduced into the computer memory as an image specified on a 128 x 128 rastre with 64 blackness levels. This image was observed on the display. Photographs of scenes shown on the display are given in Fig,2. Note that even where the object surfaces had a two-gade pattern (Fig, la, b) the image introduced into the computer was halftone (Fig, 2a, b) due to both the optical properties of the camera and the action of automatic focusing.

The image was divided into 77 52 x 20 fragments. The centers of the fragments were spaced by 10 rastre cells horizontally and 16 cells vertically. The windows which cut the fragments were 50% overlapping both horizontally and vertically. The values of the x_R vector components were computed for each fragment on a 29 x 17 rastre for four shift directions. In each direction the shift was by I, 2 or 3 cells. Consequently, each fragment was characterized by a 12-dimensional vector. To reduce the time for processing the values of x_R the computation was performed for 100 points randomly selected within that rastre rather than for all points of the fragments rastre. These points were different for various fragments. As special experiments have shown, this reduction did not lead to substantial differences in classification.

The totality of all vectors obtained from one image was divided into 4-8 classes.

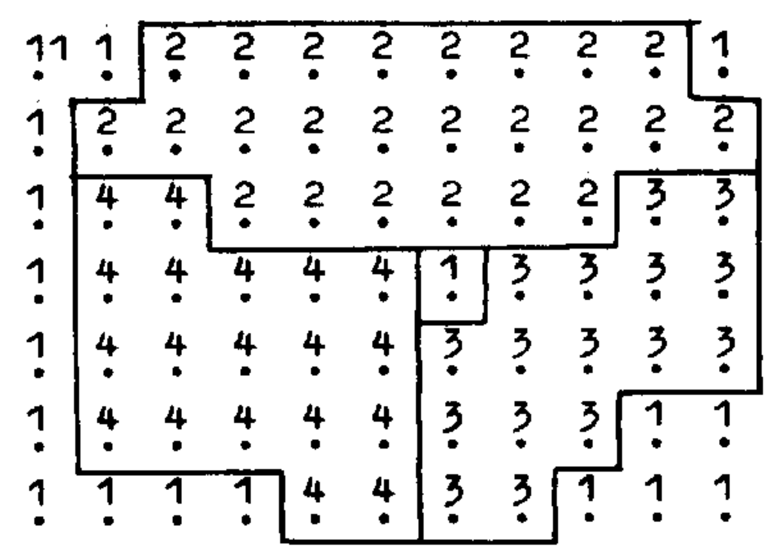
The correctness of the processing results was estimated visually in terms of correspondence areas identified and the surfaces of objects.

Results

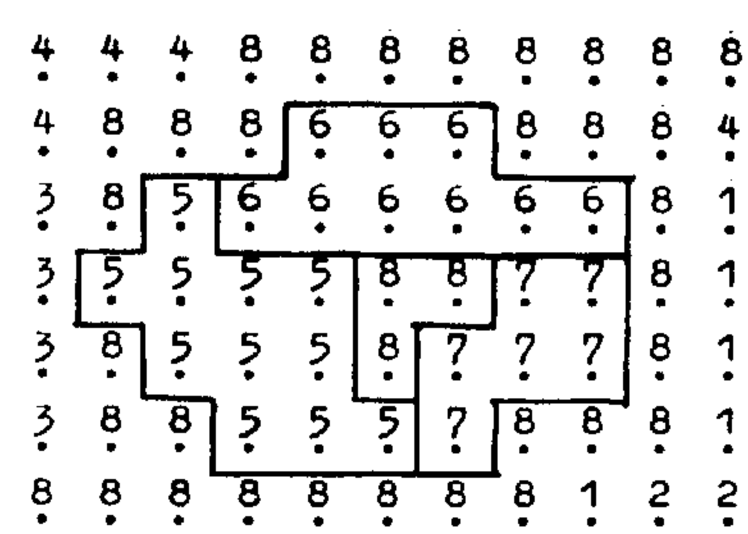
Fig.3 shows the results of marking the images of scenes (see Fig,2) by symbols associated with the scores of classes.

In the image of two cubes whose surfaces are patterned by lines and square spots (Fig.2a, b) all the three surfaces were identified (Fig.3a,b). The processing resultB have a number of interesting features. In each case the fragments on the meeting point of identified areas where picked out. These fragments (a fragment of the first class in Fig.3a and three fragments of the eighth class, Fig.3b) are in the vicinity of the cube apex. Almost all fragments of the eighth class in Fig. 3b incorporate a boundary of areas of different texture.

In the image of a pin with a nut screwed on it an area was identified which is associated with the thread surface (fragments of the third class in Fig.3c). Besides, background areas (fragments of the fourth class) could not be separated because the texture

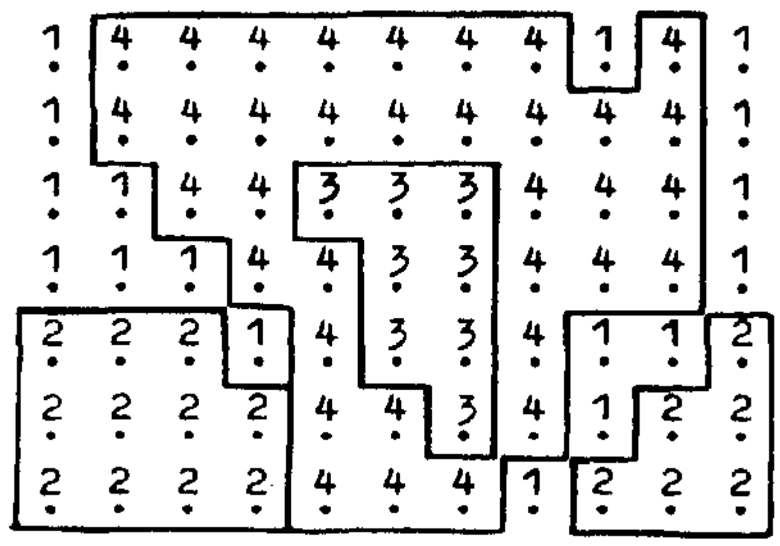


(a)

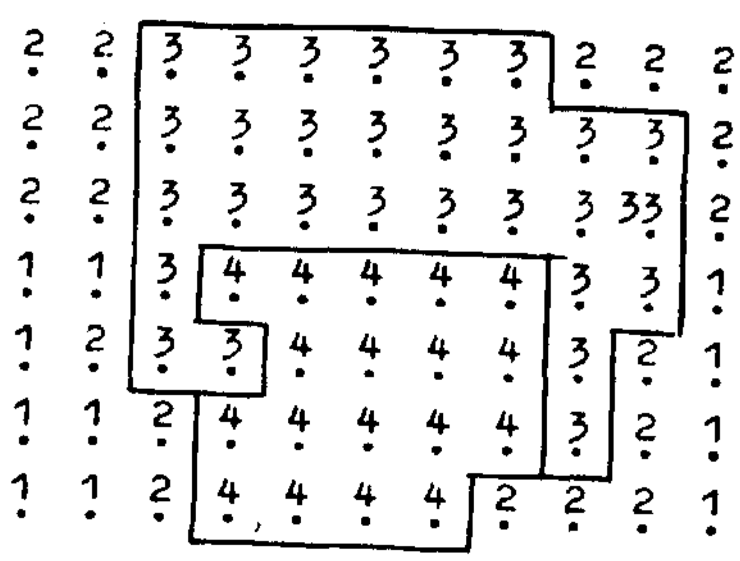


(b)

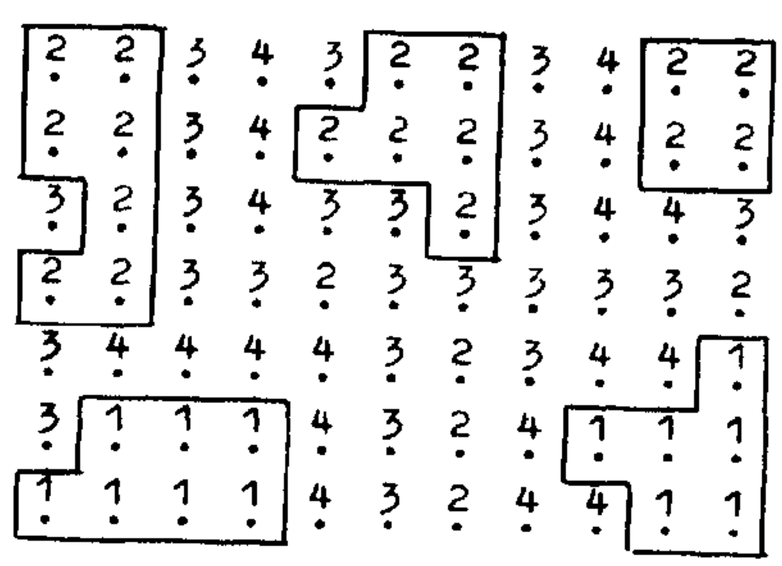
Figure 3



(c)



(d)



(e)

Figure 3

of these surfaces is too fine for the camera resolution. They can be separated by analyzing the blacknes intensity. However, as seen from the formula for computing the vector x_R its components do not change with the fragment mean blackness intensity.

In the image of a stockpile of similar nuts (Fig. 3d) an area associated with the internal thread surface (fragments of the third class) and an area assotiated with the external surface (fragments of the fourth class) were identified. The background areas covered too small an area in the image. Therefore in this case it is difficult to say how successfully the background areas (fragments of the first and second class) were identified.

In the image of the scene of Fig.le details of both typeB (in Fig.3a fragments of the first and second class respectively) were identified. Fragments of other classes contain either parts of boundaries between the objects and the background or small partions of the background.

This leads to the conclusion that the described procedure can be used as one of the algorithmical tools for design of a robot systems analyzing real three-dimensional scenes.

References

1. Tsuji S., Tomita F. A structural analyser for a class of textures, Computer graphics and image processing, v.2, n.34, 1973» pp.216-231.

2. Bajesy R., Computer identification of visual surfaces, Computer graphics and image processing, v.2, n.2, 1973, pp.118-130.

3. Vainshtein G.G., Methods and hardware of automatical analysis of images in robot control problems. In "Robots-manipulators for automatization of manual and auxiliary Jobs", "Mashinostrojenie", 1972, (in Russian).

4. Dorofeyuk A.A., Teaching algorithms for a pattern-recognition machine without a teacher based on the potential function method. Automation and Remote Control, n.10, 1966.

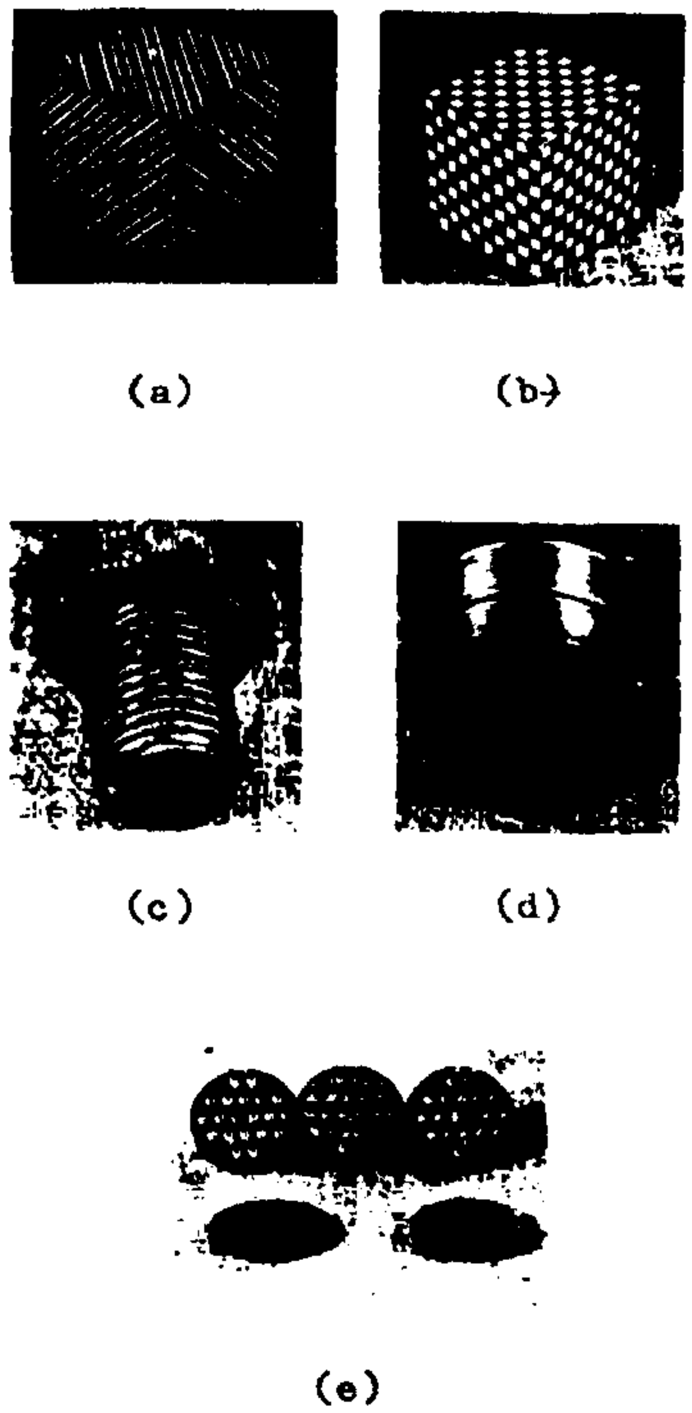


Figure 1

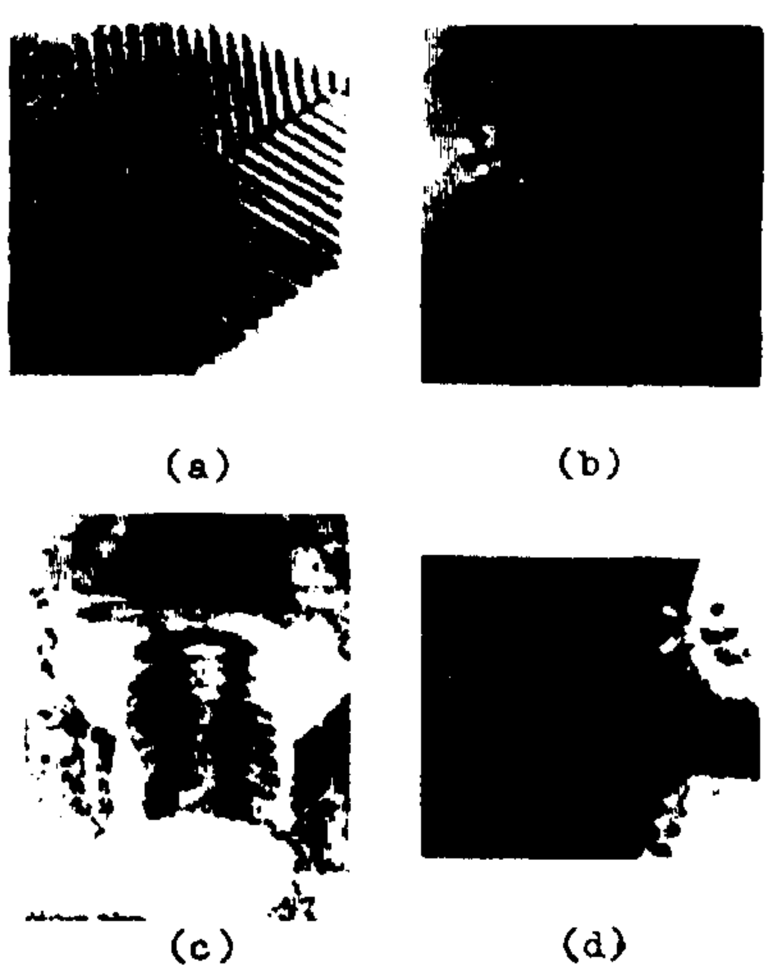


Figure 2