Robotique minière : application de la vision par ordinateur à l'automatisation d'une machine d'abattage

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MINING ROBOTICS :
Application of computer vision to the automation of a roadheader

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Abstract — **Automation of mining operations involves the use of sensing, remote monitoring and control systems in order to confront a variety of situations and environmental conditions.**
The need of profitability of a mine sometimes requires that selective cutting be performed in order to separate rich ore from waste at the cutting stage.
Basically, the problems to be solved are those of modelling an uncontrolled, changing mine environment and programming the machine to cut a pattern accordingly.
We present in this paper how image segmentation and classification, 3D scene perception and path planning can cooperate to solve such a complex problem as selective cutting.

1 INTRODUCTION

This work has been performed in the framework of a collaborative program [1] funded by the Commission of the European Communities; AITEMIN, LAAS-CNRS and INERIS have undertaken a research project to automate the cutting operation of a roadheader for selective cutting in an underground potash mine near Barcelona in Spain [4].
Many types of mining require cutting to be performed in a selective manner for

several reasons : different unloading points for rich ore and waste, cutting efficiency, roof support, and safety. The possibility of automating selective cutting is very interesting for the economic benefits, but requires an accurate and reliable "face mapping".
The system we describe is based on the use of computer vision to discriminate the different ore types found in the face (sylvinite, carnalite and salt). Using the information about the ore distribution, paths are then planned for the computer controlled cutting tool (called 'boom' in the sequel).
We present in this paper the solutions that have been chosen for performing selective cutting automation. These solutions go beyond the framework of our application and can be extended to any automation problem involving image processing.

2 DESCRIPTION OF THE APPLICATION

In Figure 1, we show a typical cross-section of the different seams.

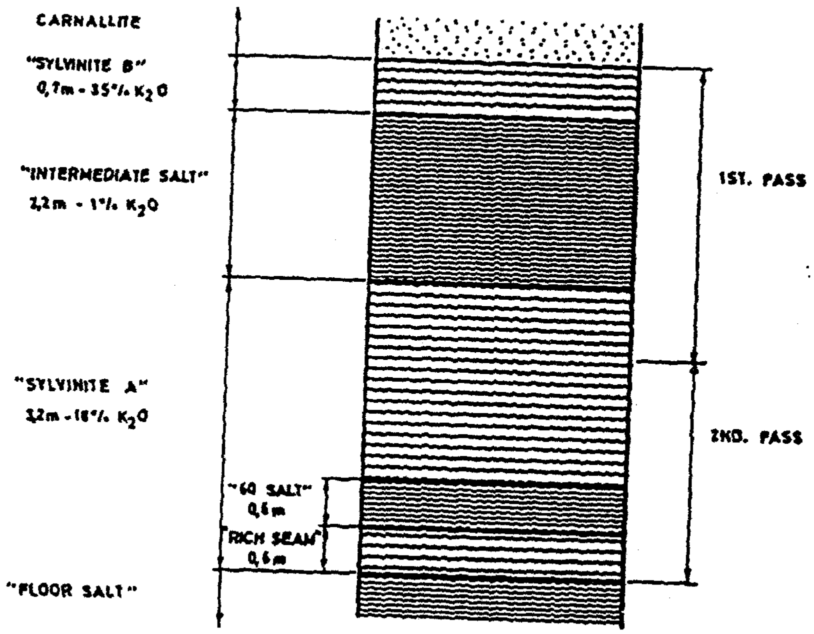

Figure 1: *Typical cross-section of the seams*

The selectivity in the cutting operation is based on cutting and separately loading the sylvinite A and B seams (rich ore) and the intermediate salt (waste), cutting as little as possible from the carnalite roof (for roof support reasons) and the floor salt. The system must be able to recognize the mineral distribution at the face, producing a "face map" which is used to determine the optimal cutting trajectory that should be performed in an automatic mode under the system control. The objective is to fit a roadheader (see Figure 2) with all of the sensors (cameras, angle sensors, ...), actuators, control equipment and data processing capacity, and then, to automatically perform selective cutting operations at a typical face of the mine.

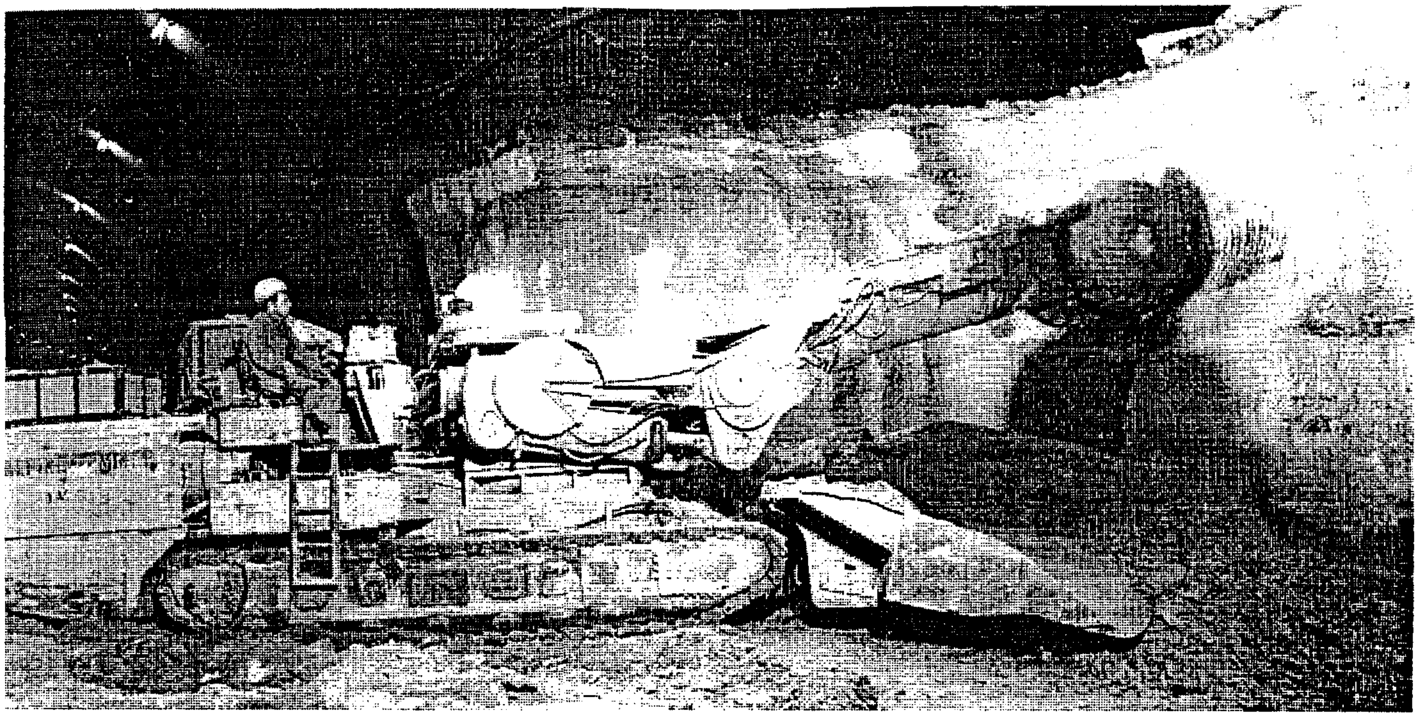

Figure 2: *Roadheader Alpine AM-100 in action*

This automatic selective cutting operation will be as follows.
Once the machine has been put into position in front of the face (the cutting head just touching the face), the system will perform the image acquisition and processing tasks : geometric distortion correction, image fusion, ore recognition, face mapping and cutting planification.
Then the machine must advance, while cutting tool cut the penetration slot from side to side; before actual cutting, geometrical transformations will be applied to the cutting plan, based on angle and distance sensors values to take into account the machine new position and attitude. Next, the cutting plan is executed.

3 ORE RECOGNITION

Human workers seem to achieve the recognition of the different ores present in the face by using the *color* information (sylvinite has a more "red" aspect than salt, which is rather orange or white) and the *texture* information (the seams of sylvinite present an important stratification).
We have tackle the problem as a pattern recognition one.
Each pixel of the image is represented by a set of features (vector $\overrightarrow{x}$) and the classification is obtained using a Bayes classifier. For each class C_k, a set of training observations which class membership is known, allow to determine parameters for

the discriminant function $f_k(\overrightarrow{x})$: the Bayes decision rule classifies a point to class C_k if and only if :

$$f_k(\overrightarrow{x}) < f_s(\overrightarrow{x}) \qquad \text{for all} \quad k \neq s$$

The key point of such an approach lies in the choice of the features which can be as much discriminant as possible to lead to a good classification result. We extract color and texture features by the following methods:

- *Color features*:
  in order to design the most effective image processing based on color characteristics, a preliminary spectral analysis has been implemented on a set of mineral samples requested to the mine [4].
  The study concluded that a discrimination between the ores could be achieved by computing at every point of the face the ratio :

$$k = \frac{\text{reflectance at 625 nm} \pm 25 \text{ nm}}{\text{reflectance at 525 nm} \pm 25 \text{ nm}}$$

  To be implemented practically, since 525 nm and 625 nm match closely the green and red filters of a color CCD camera, we have approximated the k ratio by dividing point by point the red and green planes of a color image (image called "R/G"). Figures 3 shows a color image of the face and Figure 4 shows the corresponding red/green image.

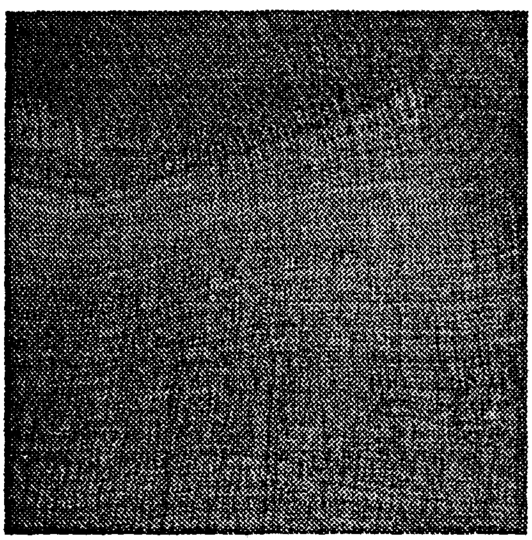

Figure 3: *A color image of the face*

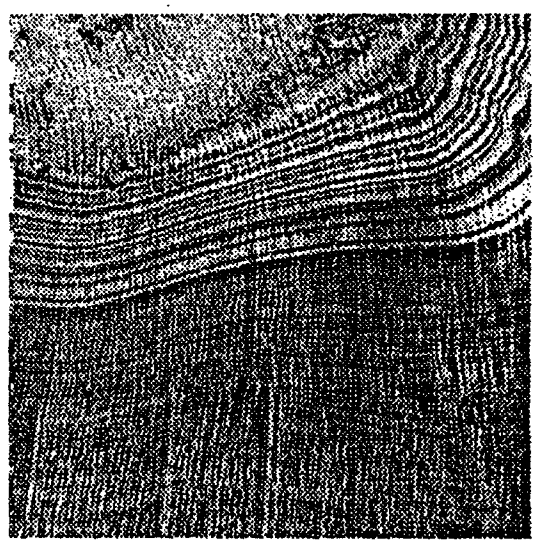

Figure 4: *R/G image from image 3*

  The R/G feature has been added to more classical color features such as (R, G, B, r, g, b, I, H, S) [2] and a discriminant analysis has shown that (r, g, R/G) were the best features for discrimination [8].

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[2] r, g and b denote normalized color.
I, H, and S denote intensity, hue and saturation.

- *Texture features*:
  we use an easy to compute texture extraction technique, inspired from Laws method [6]. First, microtexture features are obtained by filtering the input image with Laws convolution masks, one for detection of horizontal stratifications, which are the most frequent in the mine, and two others for detection of slanted stratifications. The relevant information for texture discrimination is present as the image variance of the microtexture features, computed over a 15×15 moving-window. Figure 5 shows the texture image obtained from image 4.

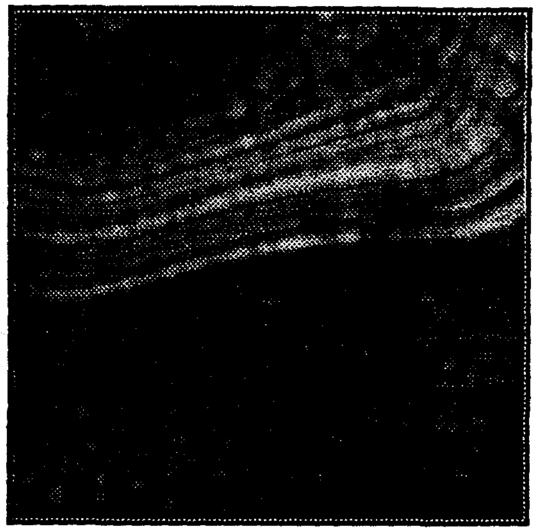


Figure 5: *The texture information from image 4*

Figure 6: *Split and Merge on image 3*

In terms of method of classification, we have chosen a "region classification" approach, which needs a preliminary region segmentation algorithm, performed with the well-known split-and-merge algorithm [5], using color uniformity predicates [1]. A region classification algorithm is applied to each region provided by the initial segmentation: each pixel of a given region is classified thanks to a Bayes classifier applied to the estimated feature vector $\overrightarrow{x}$ of this pixel; the label of the most frequently occurring class is assigned to that region.
Such a labelling process can cause the merging of adjacent regions if they are given the same label; so, we provide significant improvements of the initial segmentation, like in a split-merge-merge approach [2] [7].
In a first step, we have discarded texture information because : (i) texture is known to be time consuming, (ii) stratification detection requires high resolution cameras. Nevertheless, with a "only color approach" (results reported in [8]), numerous problems of missclassification can occurr. Figure 6 shows the result of applying the split and merge algorithm on image 3 and Figure 7 shows the result of classifying the regions on color attributes. Taking into account the texture feature has brought a

significant improvement, as shown in Figure 8.
As can be seen in this figure, a seam of carnalite has been identified at the bottom of the image which is impossible according to the composition of the deposit. Such a mistake can be easily identified, using contextual information in order to guide the segmentation process.

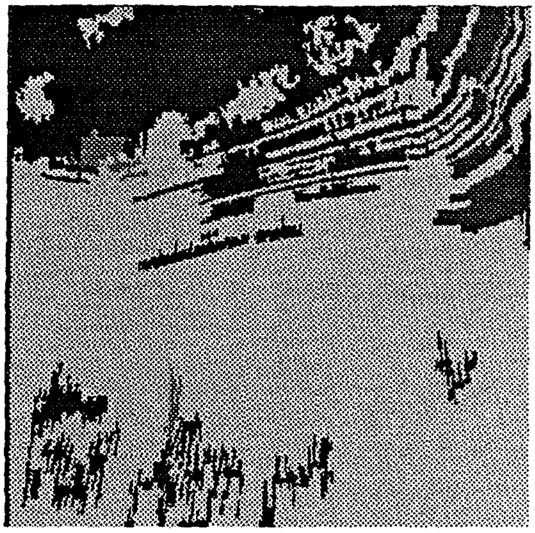


Figure 7: *Classification of the regions of image 6 on color features*

Figure 8: *Classification of regions of image 6 after adding the texture feature*

An important problem we must cope with in order to apply this approach, is the choice of good cameras. To detect stratification, thin seams of only a few centimeters thick have to be isolated from each other, on a broad face (7 m by 7 m). This simultaneously requires a *large view field* and *high resolution* cameras. The results presented previously have been obtained by the use of a 3-CCD color camera which cannot be used in an hostile environment such as a mine.

So, we must use 1-CCD camera: they will be equipped with larger lenses to provide a better resolution. The view field will be reduced but this could be compensated by using a set of cameras providing overlapping images that will be fused using the method proposed hereafter to provide a single view of the whole face.

4 3D SCENE PERCEPTION

Once image is segmented, we must produce a "face map" that can be used to control the cutting boom as determined by the ore distribution; the aim of the "face map" is to give the face mineral's map in a coordinate system fixed to the roadheader. First of all, we must be able to determine the relationship between the 3-D coordinates of a point in the face and the corresponding 2-D coordinates of its image; the modelling of the perspective transformation of the camera is required.

We have chosen a camera model derived from the classical pinhole model to which we have added quadratic terms related to radial distortion. Calling (u_d, v_d) the distorted image coordinates and (X_m, Y_m, Z_m) the 3D coordinates [3], the camera model can be written :

$$u_d = f(X_m, Y_m, Z_m) \;\; ; \;\; v_d = g(X_m, Y_m, Z_m) \tag{1}$$

Once a camera model has been chosen, the calibration phase consists of identifying the parameters of the model. Our calibration method requires the position of a set of non-coplanar points [3] in the reference coordinate system.

For this purpose, we have added artificial marks on the machine that can be easily located in the roadheader frame according to mechanical drawings and that can be easily detected in an image. An automatic calibration process has been implemented : (i) the boom is moved in the view field of the camera and at each 3D position of the boom an image is acquired, (ii) the marks are automatically detected in the image using the color information , and their 2D position is paired with their corresponding 3D position.

A set of (2D position, 3D position) pairs is used to estimate the $f()$ and $g()$ functions that match best equations (1); we have tackled the problem as a non-linear constrained optimization problem.

Once the cameras are calibrated, we can transform a face image into a face map in the roadheader machine coordinate system. All interesting 3D points lay on the face; the most convenient choice to refer to each ones, are the joint coordinates (θ_1, θ_2) of the roadheader boom. This system would make trajectory planning easier, as the boom is controlled using these coordinates.

We know that the face is a portion of a torus, and the equation of the torus

$$(X_m, Y_m, Z_m) = F(\theta_1, \theta_2) \tag{2}$$

is known in a coordinate system fixed to the roadheader.

We discretize the values that (θ_1, θ_2) can take (sampling interval is 0.2 degrees); for each 3D point obtained, we compute, using equations (2) and (1), the corresponding (u_d, v_d) image point and put in position (θ_1, θ_2) of the "face map" we are constructing the pixel value located in (u_d, v_d).

In order to cope with image resolution, it is required to set up many cameras at different safe locations in such way that they cover areas which complement each other. As a result, the data from many cameras, located at different positions, has to be combined into a single face map.

The problem of image fusion is solved naturally from the construction of the face map; from a given point of the face, corresponding to a discrete value (θ_1, θ_2), we compute, using equations (2) and (1) for each camera c_i mounted on the machine, the corresponding image coordinates (u_i, v_i); if this point is seen from more than

[3]The 3D coordinates are expressed in the a 3D coordinate system fixed to the roadheader.

one camera, the pixel value we put in the face map, is the mean of the pixel values found in the corresponding image coordinates.

Figures 9 and 10 show two parts of the same scene taken by two cameras and Figure 11 shows the result of combining them into a single image.

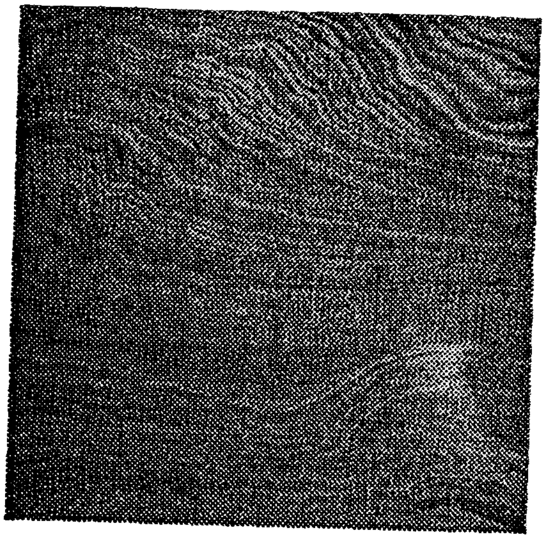


Figure 9: *Left image*

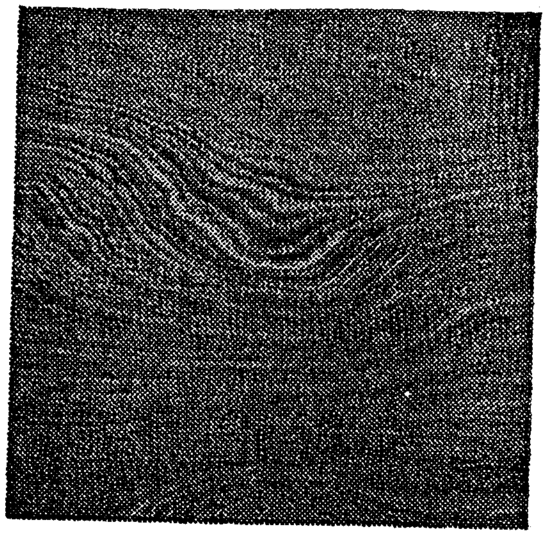


Figure 10: *Right image*

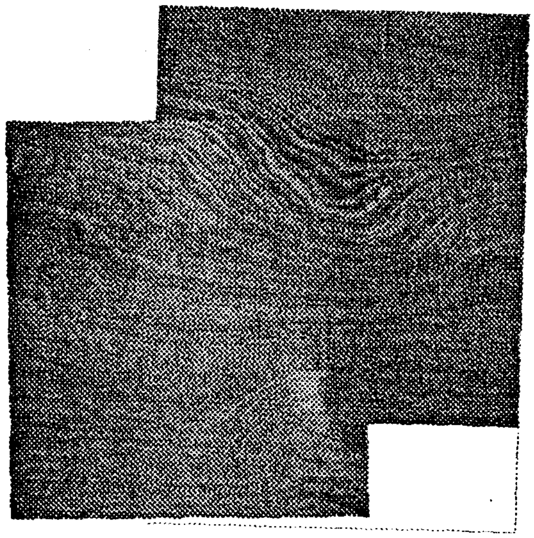
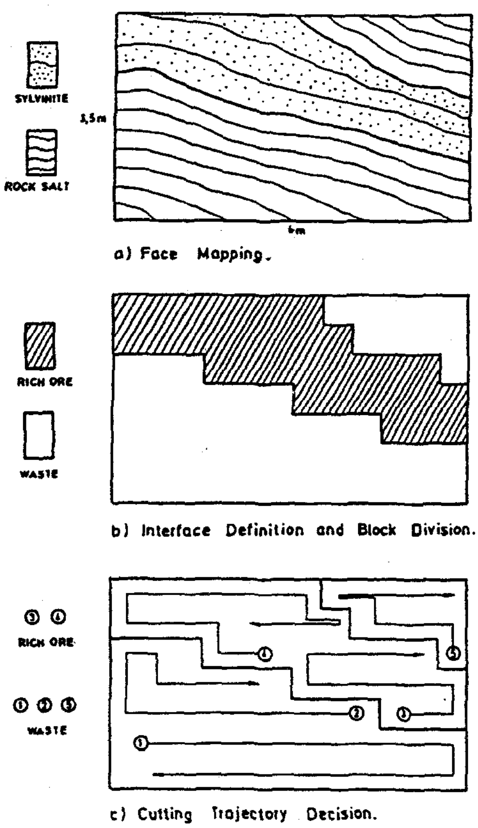


Figure 11: *Fused image*

5 Cutting Planification

Once the face map is produced, a module generates the most adequate cutting trajectory, which is in principle, different for every new cut. This module takes in account the desired final profile, roadheader operationnal limitations, and requirements of the loading procedure (shuttle car capacity). By now, no optimization criteria have been introduced in the operational planning, although the produced trajectory is intended to be an "efficient" one. As an example, the figure 12 shows a face map, boundaries redefinition according to the boom limitations and cutting plan generated for waste and for rich ore; penetration slot is not taken in account in this example.



centerline

Figure 12: *Example of cutting planification*

6 CONCLUSIONS

In this paper, we have presented an application of computer vision for the automation of cutting operations in a potash mine.

Many fields of research are involved in this project; we have shown that color and texture informations were important for minerals identification . The two kinds of information cooperate in an automatic image classification algorithm which has been validated on many images of the mine face.

At that point of our work on the "ore identification" problem, many improvements can be done to make the process more robust : particularly, the segmentation should be directed by the *a priori* knowledge we have on that application. For instance, we know that from roof to floor, the sequence of minerals is always *carnalite, sylvinite B, intermediate salt, sylvinite A and salt.* It would be a pity not to use this kind of contextual information at some moment of the identification process.

An integrated experiment involving vision, path planning for the boom trajectory and cutting operation will be done during the next months in order to demonstrate the utility of these algorithms.

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