Image Mining for Intelligent Autonomous Coal Mining

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Abstract. Automation in underground mining enhances safety and leads to economic efficiencies. After more than 50 years of research, automation tasks have gradually been growing out of the classic engineering/mechanical environment and require a sophisticated data-mining treatment.

The success of (mechanical) process automation has left only one remaining place in the coal-excavation process where human labor is still indispensable: the operation of the excavation machine, the shearer loader. The necessity to utilize human labor is due to the unknown exact position of the underground coal seam to be excavated. Therefore, at each point in time, a human has to detect the direction in which to excavate further. In the harsh underground conditions, this brings about serious safety and health hazards. The operator is surrounded by dust, which obstructs his vision, among others. In addition, human mistakes in coal-layer detection mean that more rock is excavated rather than coal, which lowers the economic efficiency of the whole coal-mining process.

In this paper we fill in the gap in the coal-excavation automation by building a pattern recognition system inside the shearer loader that turns it into a "smart" machine that is capable of detecting the correct position of the coal to be excavated and enable human-free coal mining. The success of such a system would mean that mines with very harsh human conditions could potentially become fully operational, since human presence would not any more be required for coal excavation.

Key words: Underground Mining, Coal Excavation Automation, Data Mining, Image Mining

1 Introduction

The automation of underground coal excavation process has long been in the focus of both industrial and academic research efforts [1, 2]. The necessity to automate this process stems from two basic reasons: improved safety and gain in economic efficiency. The prospect of improved safety is invaluable, where the ultimate goal is to utilize as little human labor as possible to avoid injuries and exposing miners to hazardous, noisy and dusty environment. Gains in economic efficiency have also come to the fore, as automation streamlines and speeds up the whole excavation process.

Historically, automation has been associated with better, faster and more robust coal-mining machines and accessories that facilitate the whole process and move it closer to being human-free, which is the ultimate goal. Here we propose one step on this path, namely automatic detection of the direction in which the coal-excavation machine, the so-called shearer loader, has to move forward. This step lies at the heart of human-free excavation as it intends to replace the worker where the machine cannot: performing a pattern recognition task by examining previously unseen coal face and deciding on the most appropriate excavation course. The shearer loader operator is constantly fulfilling this task, and he is doing so in very harsh, noisy and dusty conditions. With an image-analysis automation system at place, the operator can be moved away from the coal face that is being excavated. Since human-free excavation naturally requires pattern recognition capabilities, the coal-mining automation is taken out of its natural engineering habitat and augmented with data-mining research solutions. An extensive survey of data-mining techniques can be found in [3].

The proposed data-mining approach to help fully automate the underground coal-mining excavation comprises three steps. First, what is needed is a robust equipment that is able to produce the raw data, that is, to make clear images of the coal seam. It turns out that this step faces enormous challenges, which have however already been solved in the course of a couple of years [5]. Second, the images are analyzed by a novel image-recognition system that is able to extract both the necessary landmarks on the coal face and to avoid wrong landmark detections via a so-called motion-recognition approach. Third, based on the recognized patterns from a succession of images, a decision is taken on the future course of excavation and the shearer loader is instructed where to position itself accordingly.

The paper is organized as follows. Section 2 describes the longwall coal excavation process in detail and points to where data-mining research comes in handy for further automation. The next section focuses on the place in the chain of coal excavation where our contribution lies: removing the operator of the shearer loader by creating a "smart" system that replaces his pattern-recognition functions. We then give an overview of our approach, discuss the challenges it faces and present experimental results from an underground mine located in the region of North Rhine-Westphalia in Germany. The last section concludes.

2 Automation of Longwall Coal Mining

Longwall mining has become a standard technology for excavating coal from underground mines [4]. This technology, summarized in Figure 1, employs a longwall shearer which is a machine equipped with one or two cutting drums. The shearer extracts the coal by traversing a longwall face (the mined area from which material is extracted). The mined coal falls onto a conveyor and is

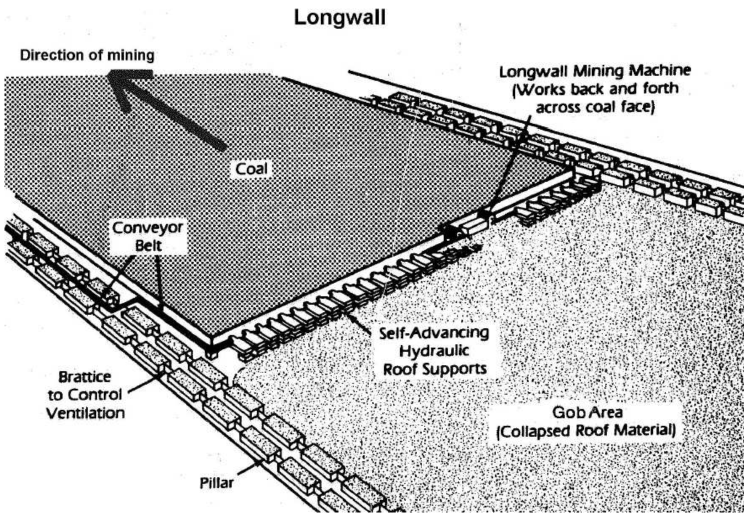

Fig. 1. The process of longwall coal mining.

transported out of the mining area. The working area of the longwall shearer is defined by roof supports. The roof supports move automatically with the shearer loader. This means that the roof behind the current coal face collapses to the so-called gob area. The longwall shearer is controlled manually by an operator (see Figure 2). Under manual control the longwall face very often detours from the coal seam. This causes unintentionally excavated rock to mix with the excavated coal, which limits the production rate. Therefore, the trajectory of the longwall shearer has to follow the coal seam as close as possible. To automate this process it is very important to estimate precisely the location of the coal seam so that the longwall shearer can be constantly repositioned accordingly.

We concentrate on automating a particular part of the longwall automation process in Figure 1, namely the langwall mining machine, which in our case is a shearer loader. The machine is able to operate on seams between 1.5 and 6 meters high, depending on the geology of the mine. At each cut, which takes place along the face of the coal seam, the machine advances, or "wins", between 80cm and 120cm into the coal seam. The automation we focus on consists of

Fig. 2. A shearer loader excavation machine in operation.

equipping the machine with hardware that is capable of taking and storing images of the coal face being excavated at each cut along the face. These images are then further analyzed by an image-recognition system augmented with motion-detection capabilities, resulting in a decision on where exactly to position the shearer loader during the next excavation run along the coal seam. The whole automation process is shown in Figure 3.

There are certain environmental challenges that the device that capture the images of the coal face has to endure, the most important being the necessity to withstand enormous vibrations and capture clear images through dust. That is why, a special infrared camera (see Figure 4) is used for that purpose.

3 Image-Analysis System for Coal Mining Automation

A crucial aspect of the the coal-mining automation process lies in the proper detection of the coal-bed boundary, which is depicted in Figure 5, leftmost image. Knowing the exact position of this boundary at each point in space is sufficient to estimate the exact position of the coal seam (based on geological domain data specific to each mine) and thus to instruct the shearer loader to advance exactly along the upper and lower bounds of the seam. Examples of three coal-bed boundaries is given in the images in Figure 5. Note that the leftmost boundary in the figure is an idealistic case that almost never occurs in practice.

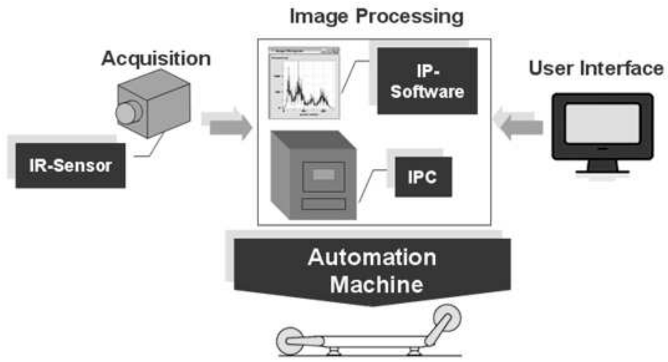

Fig. 3. Automating the coal-bed boundary detection.

A data-mining approach to recognize the coal-bed boundary is indispensable. The reason for this boils down to the fact that no two coal-bead boundary pictures are exactly alike and therefore a smart system that is able to detect previously unseen (future) boundaries based on a number of existing boundary images is required.

Fig. 4. The infrared camera used for taking images of the coal face.

The proposed image-recognition system consists of two blocks. The first block is a noise-elimination block. It detects and removes the parts of the images that represent the excavated material (most clearly visible in Figure 5, leftmost image). This is very important for the overall effectiveness of the system since the excavated material is quite random and can be easily mistaken for a true coal-bed boundary - due to possible similarities both in shape and in color. For that reason the noise-elimination block employs a motion-detection mechanism that combines information from successive images. It detects and removes parts of the images that contain random data assuming that they represent the excavated material. The next block of the image-recognition system is a coal-bed boundary detector. It is essentially a histogram density estimator. The detector receives cleared images from the noise-elimination block and then detects the coal-bed boundary. The two-stage process of the image-analysis system is demonstrated in Figure 6.

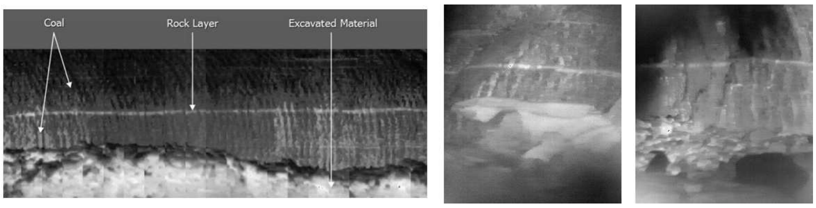

Fig. 5. Examples of coal-bed boundaries.

One of the open questions is what criterion to use to evaluate the quality of the automation system. Usual statistical criteria, such as mean square error between the true and predicted coal-bed boundaries do not have an immediate practical value as they do not relate to measures such as improved safety, increased speed of cutting, and loss of coal deposits that are not excavated. For

Fig. 6. A two-step detection process of a coal-bed boundary.

the time being, therefore, it is up to the subjective evaluation of experienced engineers and miners to decide, based on the differences between the true and predicted boundaries, on the quality of the automation system. With that in mind, the real-life results from a mining site in North-Rhein Westphalia so far point to the enormous improvement in safety and economic value from removing human workers that operate the shearer loader and replacing them with an automation system.

4 Conclusion

The full automation of underground coal mining is a key task for the underground mining industry at large. During the last 50 years the level and sophistication of automation has reached a stage where engineering solution have to be combined with advanced data-mining solutions in the quest of creating a human-free coal mining process. We have proposed a solution to one aspect of the automation process that requires a data-mining approach to make predictions of future, unknown states, namely automatic detection of the coal-bed boundary based on images from an infrared camera that is installed on a shearer loader excavation machine. Future research in this area can be directed into combining multiple sources of sensor information about the coal bed, such as radars, inertia-measurement devices, etc. so as to make the automation process even more robust and reliable.

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