Selected methods for material identification on the border of geological layers for the automation of industrial processes of obtaining raw materials

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Abstract. Production plants wishing to become competitive on the local and global market should offer their products at the lowest possible price and, at the same time, in the highest possible quality. One of the key tasks for the engineering and technical staff working on them is improving the organization of work and the degree of use of means of production, allowing to increase work efficiency. The latest technological achievements focused on the concept of the Industry 4.0 create new opportunities for further improvement of production processes, their optimization, reduction of costs, or reduction of the nuisance of physical work and mental effort of employees. Many industries use both renewable and nonrenewable natural resources available on earth. Acquiring some of them requires considerable resources and is very burdensome for people. Especially regarding resources deep underground. In the near future, we will also use material resources obtained from outside the Earth, which is an additional challenge. Therefore, the integration of the latest technologies, especially in the field of automation and autonomous robots, IoT and Big data is becoming an essential research area.

The paper presents an overview of technological methods and solutions of material identification that can be used in the processes of automated sourcing of materials on an industrial scale. Particular attention was paid to techniques that can be used by specialized, autonomous robots working in conditions that are hard and unsafe for humans. Discussed recognition systems can use advanced methods and the latest technologies. They are most often implemented using special sensors installed on or close to the executive element of a machine. The differences in rocks hardness and compressive strength allowed for the development of methods using acoustic waves and also methods using the measurement of vibration of the cutting tools and machine parts on which they are installed. Another method uses the natural features of rocks adjacent to the seam being extracted - it measures differences in the level of radioactivity. On this basis, a method was developed based on the recognition of low gamma radiation activity. Methods based on the use of radars or thermal imaging cameras testing the temperature of cutting knives installed on the cutting body were also proposed. Another interesting solution is the optical touch sensor that recognizes different types of rock layers. Difficult working conditions, also for machines, in which there is a high concentration of stone dust limiting visibility, the presence of water, and high noise generated by working devices, reveals a number of advantages and disadvantages in the above methods to use them in autonomous, robotic solutions.

1. Introduction

During several years, Polish and global companies are constantly changing, the reason for these changes is the wider implementation of information technologies. The idea of Industry 4.0 is
becoming more and more popular and it already has, or will have a significant impact on most companies and their employees in the near future. The influence of similar technological revolutions was visible in many areas, not only in industry, but also in science, medicine, agriculture and trade, among others. We can distinguish several most important elements without which the idea of Industry 4.0 could not function, they are: computing clouds, large data sets, Internet of Things, augmented reality, simulation, digitization, all kinds of autonomous solutions, human-robot cooperation, and integration of sensors with artificial intelligence. The Industry 4.0 concept can broadly be defined as the transformation of separate automated production plants into fully automated and optimized production environments. Production processes are combined within the existing systems in enterprises. It integrates sensors, devices and IT systems into the value chain within the company boundaries. Such factories have the ability to autonomously exchange information through the use of Internet communication protocols, thus reacting in real time to potential errors and adapting to changes in consumer demand for products. Smart factories improved in this way ensure the production of high-quality products at competitive prices, and the investment in them quickly pays off [1].

Highly automated production processes should be properly monitored and supervised to avoid and detect potential failures as well as to obtain the desired final product. For this purpose, sensors are used as "sense receptors" in the current technology, but also directly by humans in the assessment or measurement of physical quantities. In fact, a measuring sensor is the first element of a measuring chain, most often consisting of several transducers. Sensors used in industrial automation systems can form complex subsystems, for example, nodes or networks. The sensor node collects signals from the sensors, processes them, stores them, and forwards them to other sensor nodes and to the control station using an agreed protocol. A sensor network is a complex system that integrates multiple independent sensors with individual or common signal processing electronics [3].

There are six basic types of signals measured by sensors [3,4]: mechanical, thermal, electric, magnetic, radiation (including electromagnetic radio waves, microwaves), and chemical (figure 1). The range of measured quantities is closely related to the operating principle of the sensor used. Defining the measured values and their measurement enables obtaining important information about the implemented process, the condition of machines, tools and equipment.

| Mechanical | •position, speed, acceleration, force, pressure, mass, density, pressure, bending moment, volume, shape, roughness, viscosity, wave amplitude, phase, polarization, spectrum |
| Thermal    | •temperature, flux, specific heat, thermal conductivity |
| Electric   | •electric charge, current, potential difference, electric field, conductivity, electric permittivity |
| Magnetic   | •magnetic field, magnetic flux, magnetic permeability |
| Radiation  | •energy of intensity, emissivity, type of radiation, reflectivity, transmittance, wave amplitude, polarization, spectrum, wave speed |
| Chemical   | •chemical composition (identifiers, concentrations, states) |

Figure 1. Measured values in the production process [2, 3].
One of the consequences of technological development is the increased demand for raw materials. The amount of raw materials used, especially metals, is constantly increasing, so it is necessary to search for new deposits of raw materials. Raw materials are sought at ever greater depths, such as copper deposits, in new areas where no mining has been conducted so far. Space is also very attractive and more and more realistic in the near future. Advanced research is already being carried out to identify and recognize the possibilities of acquiring its resources. Due to the huge distances to travel in space, the resources available on the Moon, Mars and the asteroid belt are considered in the first place. These raw materials do not necessarily have to be transported to the Earth - their processing and use can also be carried out in space, as is planned, for example, during the expansion of bases on Mars, where sending all necessary materials from Earth is very expensive. Lunar regolith is rich in helium isotopes, which is an ideal fuel for a thermonuclear reaction. Asteroids are rich in iron, nickel, cobalt and platinum group metals. As automation develops, the tasks of sourcing raw materials in this way are becoming more and more real. [4]

One of the fundamental problems of the above-described issues in the area of the autonomous and automatic process of obtaining natural resources is the ability to correctly identify the boundary between geological layers during extraction, to obtain the desired raw material in the least polluted form. Various methods can be used to identify the boundary between the useful layer and gangue, based on the assessment of rock properties such as: hardness, natural radiation, electrical conductivity, reflectance. The article presents an overview of the most popular (on Earth) methods of recognizing the boundary between geological layers of rocks. The selection of an appropriate method of recognizing rocks and the boundary of individual layers and the corresponding hardware implementation in the form of sensors is crucial in developing effective automation tools for the operation process under given environmental conditions (e.g. temperature, pressure, dust, and chemical composition of the atmosphere).

2. Methods of recognizing the boundary between geological layers

2.1. Natural gamma radiation

Radioactivity is the ability of the nuclei of some elements to spontaneously convert into others, through the gradual decay and reduction of atomic nuclei. Radioactivity is most often associated with the emission of alpha and beta particles and gamma radiation. The α, β and γ rays differ from each other in the degree of penetration:

- Alpha rays are blocked by an aluminum plate with a thickness of 0.04 mm or an 8 cm air ring
- Beta rays pass through a 5 cm thick aluminum plate
- Gamma rays have the greatest penetration, penetrating through an iron layer 30 cm thick and able to ionize the air

Radioactive elements with their isotopes are arranged into five families: uranium-radium, actinium, thorium, neptunium, and potassium. In terms of radioactivity, there are three types of rocks that are characterized by:

- low radioactivity - sands, sandstones, limestone, dolomite, salts, anhydrites
- medium radioactivity - clay, clays shales
- high radioactivity - clay shales, bentonite

The method of recognizing the boundary of rock layers based on the natural occurrence of γ radiation can be most used in the detection of coal and rock. Based on the research [5], it was found that the rocks surrounding the coal seams are characterized by an increased value of radiation. The concentration of radioactive isotopes observed in coal rocks are several times higher than the values recorded in coal. Table 1 shows the range of variability of the specific activity of natural radioactive isotopes occurring in Poland. Coal radiation values are several times lower than the rock layers surrounding the seam. The difference in radioactivity can therefore be used to develop the concept of recognizing the boundary between the layers. Recognition can be carried out using a detector installed on the combine arm. For the correct determination of the limit, it is necessary to take samples and
determine the radioactivity value for coal and rock. Based on the determined radioactive background, the sensor recording radiation from rocks with the use of appropriate software controlling the combine's arm will enable its automatic operation [5-7].

Table 1. The range of variability of the specific activity of natural radioactive isotopes in coals and rocks [8].

| Layers                  | $^{226}$Ra | $^{228}$Ra | $^{40}$K |
|-------------------------|------------|------------|----------|
| Coal                    | 7-48       | 5-19       | 24-93    |
| Mudstone i shales       | 51-120     | 59-117     | 393-1070 |

2.2. Vibration measurement method

Each process of obtaining natural resources is carried out by installed machines, their work generates vibrations that can be measured. Vibrations are usually low amplitude and low frequency vibrations up to several dozen Hz. Vibration measurement is more and more often used in measurement diagnostics of machines and devices, allowing for early detection of failures. The most popular sensor for measuring vibration is the accelerometer. There are three types of accelerometers, the names of which are derived from the measurement method used in them: piezoelectric PE, variable capacitance VR, piezoresistive PR [8].

Piezoelectric accelerometers are the most popular type of sensor used in the industry to measure vibration. They use the piezoelectric phenomenon in crystals, when a mechanical load occurs, an electric charge is created in the crystal. Systems of this type are characterized by high sensitivity and are used in seismic measurements, crash tests, and destructive tests carried out in extremely difficult conditions [8,9].

Capacitive transducers made in MEMS (Mikroelectromechanical System) technology use changing capacitance depending on the position of the moving plates. These are the smallest and cheapest sensors available on the market, used primarily in mobile devices and consumer electronics. Their disadvantage is the low accuracy of measurement for signals with higher frequencies and amplitudes, therefore they are not used in industry. Due to their small size, they are used mainly in mobile devices and in consumer electronics [8, 10-12].

Piezo-resistance accelerometers - they measure the value of electrical resistance, which varies depending on the mechanical load. They are characterized by a wide measurement band allowing the registration of high-frequency vibrations, and due to the ability to measure slow-varying signals, they are used in simple inertial navigation systems [8, 12].

Laser vibration sensors are used when the sensor cannot be installed on a running device. The principle of operation is based on comparing the laser beam reflected from the tested object and reaching the photodetector. The laser vibrometer provides non-contact measurement, eliminating interference caused by the weight of the sensors and the measurement temperature. The measurement can be made with high accuracy from a long distance [8, 12].

The rock layer obtained by the mining machine causes it to vibrate. Each geological layer that is exploited has different vibration characteristics depending on the hardness of the rock. The rock identification system consists in installing accelerometers on the mining device. Vibrations to which the machine is made during operation are recorded by sensors and monitored to detect when the desired layer is left [13, 14].

2.3. Acoustic method

The acoustic wave method is similar to the vibration method. Sound recording is used instead of measuring vibration by an accelerometer. Rock layers have different values of compressive strength. During mining, a rock with a higher compressive strength generates a higher amplitude of the
measured signal. It is therefore possible to distinguish rock layers with higher and lower strength. To make it possible, we need to complete samples of signals for given rock layers, the differentiation of which we are interested in. Such samples serve as training samples for the neural network. The neural network is designed to compare training samples with samples measured during mining so as to control the mining process in the intended layer [15, 16].

2.4. Optical method
Widely used vision and thermal imaging cameras can be used to define the rock layer. A camera installed on the cutting device records the image or the temperature of the cutting knives. The recorded image is analyzed to detect the difference in the textures of the rock layers. Texture analysis is about finding and extracting from an image the texture characteristics of various objects. The next step is to calculate the value of the texture features based on the gray space coexistence matrix method. There are vectors of texture features such as energy, contrast, correlation and entropy. The energy mainly reflects the gray distribution of the image and the roughness of the texture. If the energy is high, the texture is rough. For rocks with a smoother texture, the energy is lower. Figure 2 shows the differences in rock texture using the example of mudstone and coal layers. Recognition can be by means of a neural network trained with a texture function. The difficulty for this method is keeping the lens clean, which is not an easy work when mining rocks [17, 13].

![Figure 2. Picture of different textures of rocks with the example of mudstone and coal.](image)

2.5. Ground penetrating radar
The GPR method belongs to the geophysical radiofrequency methods. Currently, the most widely used are pulse georadars. The measuring equipment consists of a central unit and two transmitting and receiving antennas. The radar emits an electromagnetic pulse of relatively high peak power and short duration. The depth range increases with the amount of energy of the generated pulse. The GPRs use antennas with frequencies from 10 MHz to 2 GHz. Antennas with a frequency of 400 MHz enable the registration of useful information up to a depth of approx. 8 m. Antennas with higher frequencies of about 1 GHz can only record up to about 1 m, however, at the expense of a smaller depth, a higher resolution of the order of centimeters is obtained. Waves propagating in the geological center are reflected, refracted and attenuated. The effectiveness of GPR operation depends on two parameters of electrical conductivity and the dielectric constant. High values of electrical conductivity reduce the radar's ability to penetrate. Electrical conductivity mainly depends on the water content, the amount of dissolved salt, the density and temperature of the material. The dielectric constant measures the ability of a material to store an electric charge when an electric field is applied to it. The condition for effective registration of useful information is the contrast against the dielectric constant between the
examined rock layers. The greater the contrast, the greater the amplitude of the reflected wave. For air, the dielectric constant is about 1, for rock layers it ranges from a few to a dozen. The distance of the GPR from the measured layers should be reduced to a minimum and its value should not exceed 10 cm. By measuring the time needed to reflect the radar wave from the transmitting antenna to the receiving antenna, the thickness of the examined rock layer can be determined. Table 2 presents the values of electric permittivity and electric resistance for rocks [13, 18-20].

| Group of rock | Rock    | Resistivity [Ωm] | Relative dielectric permittivity |
|---------------|---------|------------------|----------------------------------|
| Pyrogenic     | granite | $10^2-10^3$      | 5-9                              |
|               | syenite | $10^2-10^5$      | 7-14                             |
|               | diorite | $10^2-10^8$      | 8-9                              |
|               | gabbro  | $10^2-10^5$      | 18                               |
|               | basalt  | $10^2-10^6$      | 12                               |
|               | peridotite | $10^2-10^3$ | 7                                |
|               | quartzite | $10-10^3$      | 7                                |
| Metamorphic   | gneiss  | $10^2-10^7$      | 8-15                             |
|               | marble  | $10^2-10^3$      | 8                                |
|               | limestone | $10^2-10^6$   | 8-15                             |
|               | dolomite | $10^2-10^6$   | -                                |
|               | sandstone | $10-10^8$     | 9-11                             |
| Sedimentary   | sand    | $10-10^{10}$     | 4-6                              |
|               | clay    | $10-10^6$        | 7-12                             |
|               | slate   | $10-10^2$        | 6-8                              |
|               | coal    | $10^2-10^3$      | 3-15                             |
|               | lignite | $10-10^3$        | 4-5                              |

3. Development of measurement results

Data from sensors installed on rock mining devices must be subjected to appropriate analysis so that they can be used to identify what rock is being cut. Proper selection of the sampling frequency is the basis of digital signal processing. According to the sampling theorem, the maximum signal frequency must not exceed half the sampling frequency. The signals received from the sensors are highly non-linear and non-stationary. The most frequently used methods of digital signal processing for non-stationary signals are: Short Time Fourier Transform, wavelet transform, Wigner-Ville transform [23]. For each signal, features representing relevant information about the signal are extracted. The final step is to train the neural network through the collected test samples. At the stage of training the neural network, the test samples of specific rocks are compared with the samples supplied by the sensor. A neural network can be trained to solve tasks such as recognition, sound, texture and vibration.

4. Conclusions

Identifying the boundaries of geological strata is an important task in the development of an automatic and autonomous system for obtaining raw materials. The article discusses the most popular groups of methods and the tools used in them. The selection of the appropriate method very strongly depends on the type of material obtained and the environmental conditions in which the extraction is to be carried
out. Sensors detecting natural gamma radiation can be used mainly for detecting the boundary of carbon and rock. It has a good detectability, but requires the collection of many measurement samples for background determination. With the global trend to move away from coal-based energy, this method may no longer be useful. Recognition by means of acoustic waves and vibrations is highly effective, they are relatively cheap methods that do not require the use of complicated technical solutions. Recognition based on the analysis of camera images has good effectiveness, but has little chance of being used in dusty conditions. The use of radar is the most expensive solution with high detectability. However, the closest possible distance between the sensor and the measured rock layers should be ensured, which is not always possible. Another problem when developing an autonomous system for obtaining raw materials is the need to process a very large amount of data obtained from various sensors in a short time. Artificial intelligence tools are suitable for such analyzes. In further research, it is expected to develop conceptual versions of the recognition system using various AI tools, especially artificial neural networks.

5. References

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