Detection of Coal Level in Underground Coal Bins Using an Improved Edge Detection Algorithm

Xin Yuanfang, Jiang Yuanyuan, and Liang Zhe
Department of Electrical and Information Engineering, Anhui University of Science and Technology, Huainan, 232001, China
Email: xinxian79@163.com, 64751700@qq.com, 651091295@qq.com

***Abstract*—Coal level testing in underground coal bunkers is always a key and difficult part of safe coal mining operations. A coal level detection system based on the high performance TMS320DM642 digital signal processor chip combined with a bidimensional empirical mode decomposition image edge extraction algorithm and mutual information is introduced. The algorithm combines the efficiency of the edge alignment method and the accuracy of the maximum mutual information method. The details of the original image are better reflected while effectively retaining the image edges. The testing system is not contact with the material. The system can function in real time and demonstrates high accuracy.**

***Index Terms*—Coal Level of Coal Bin; DM642; Bidimensional Empirical Mode Decomposition; Edge Extraction**

I. Introduction

In the process of coal production, the coal bunker must be set up in all major underground and surface transport links to ease the ascension transport inequality of each link. Therefore, coal bins in underground bunkers are seen as the throat of production in coal mines. Its risk positions and short positions is a greater threat to safety production. Therefore, timely and accurate monitoring of underground coal bunker coal levels is critical to ensuring safe and efficient production.

With the continuous development of coal mine production, according to the specific underground coal installation environment, on-site conditions and the state of the measured medium, etc. Various methods, such as capacitor electric, hammer type, ultrasonic type and microwave method, have been used to test the coal in the bunker. These methods have rigorous standards for temperature, protection, depth-to-width ratio etc. It is difficult to achieve precise positioning over a period of time for underground coal.

Due to space limitations, the diameter of the underground bunker is approximately 5 to 7 m. The height is approximately 40 m, and some are up to 80 m deep. Due to the high dust concentration when unloading coal in a warehouse, significant humidity is required to avoid excessive exposure to dust. This makes it for pulverized coal to stick to the warehouse walls. As coal sticks to the silo walls for a long period of time, the walls become very rough. Thus, it is difficult to distinguish between the coal and the silo wall. Furthermore, the unequal production of each link and different ranges of the coal's natural rest angle can lead to the coal face in the bunker haying different shapes. The bunker coal level changes very slowly. It can change by one meter every few minutes or every few hours. Currently, underground coal bunkers do not have any lighting. Thus, the condition of the coal in the bunker cannot be identified by the human eye. It can only be seen with an auxiliary light source.

As the development of coal mining continues, the following basic requirements should be met:

1) Sufficient capacity can guarantee smooth circulation of coal in the warehouse.

2) Forms of protection should correspond to each warehouse structure and production chain.

3) The production maintenance should be minimized within the effective service duration.

Underground bunkers have low illumination, high volumes of dust and high humidity. Therefore, image processing technology to detect levers in underground coal bunkers has been limited. However, with the development of image recognition technology, computer vision technology methods have been developed to detect material levels with an auxiliary light source. In this paper, a coal detection scheme is introduced. The scheme is based on an analysis of existing coal bunker level measurement methods according to the characteristics of an underground bunker. The proposed method employs a high performance DM642 digital signal processor (DSP) chip as the core and combines the range gated laser imaging technology and image processing recognition. The principle of work is the fixed beam that measurement required is produced by the laser. The beam forms feature points on the coal's surface. When the coal bit depth changes, a spot is formed on the surface of the intensified

Foundation item: Colleges and universities in Anhui province natural science research project (KJ2013B086); Anhui university of science and technology foundation for young teachers' scientific research project (2012QNZ07).

Corresponding author: Xin Yuanfang. Email: xinxian79@163.com

doi:10.4304/jmm.9.6.796-803

TABLE I. PERFORMANCE ASSESSMENT OF COMMONLY USED COAL BUNKER LEVEL METER

Detection mode	Equipment	Anti-interference	Measurement accuracy	Maintenance
Ultrasonic	Simple	Weak	Common	Less
Hammer	Complex	Common	Common	Mass
Capacitor	Simple	Common	Common	Common
Radiation	Simple	Strong	Strong	Mass
Image processing	Simple	Strong	Strong	Less

charge coupled device (ICCD) camera as the image point position changes. According to the principles of imaging, the measured position can be calculated from the distance of the moving image point. Thus, the depth of the coal will be acquired quickly and accurately.

An improved noisy image edge detection algorithm is proposed in this paper. The algorithm combines the advantages of bidimensional empirical mode decomposition (BEMD), mutual information entropy, and image overlay. The mutual information and edge gradient features are effective for integration. First, the image is broken down by BEMD. The strength of association between the high frequency and low frequency is measured by mutual information entropy between adjacent components. If a certain amount of mutual information entropy reaches a predetermined threshold. The component will be the demarcation point between the high frequency and low frequency parts. High frequency components' edges are detected by the wavelet transform modulus maxima method. Edges of the low frequency part are detected by the mathematical morphology method [3]. Finally, the advantages of the two methods are combined, and the images are fused to obtain the image edges.

This method can strip the various modal implied according to its own information characteristics of the image. Image signal filtering can be achieved by image fusion. At the same time, the details of the image edge features are well preserved. The results show that the algorithm combines the efficiency of the edge alignment method and the accuracy of the maximum mutual information method. The details of the original image are better reflected while effectively retaining the image edges.

II. HARDWARE

Currently, the hardware implementations of image processing systems primarily have the following characteristics:

1) The system chip is based on the Application Specific Integrated Circuit. However, this technology is uncommon and expensive.

2) The hardware system is based on the combination of a DSP chip and a field-programmable gate array, which enable some programmability. However, the interface is more and the hardware structure is complex. Therefore, this type of hardware system is not suitable for a complex underground coal bunker imaging system.

3) The system structure is based on high speed DSP. It has international dimensions. The system can adjust its algorithm and relevant parameters according to a changing environment. The hardware circuit structure is relatively simple and reliable. Thus, this method is more suitable for underground bunker image processing.

Synthesizing the functional characteristics (storage interface, operation speed, calculation precision, etc.) and cost performance of each type of DSP system, and the characteristics of an underground bunker image processing system, requires a large number of arithmetic operations and high speed data transmission that can function in harsh conditions. Thus, a high-performance DSP chip system (TMS320DM642, DM642, TI Company) is used as the core processor. A hardware system block diagram is shown in Figure 1.

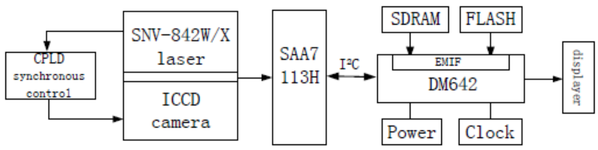


Figure 1. Hardware system diagram

The whole hardware system includes the DM642, a video conversion chip (SAA7113H), the corresponding memory chips, and the image acquisition device. This simple design can improve stability of the system and improve flexibility of the system's applications.

First, the system collects coal images with an enhanced ICCD camera using range gated laser active imaging technology. Then, the system uses the inter-integrated circuit (I^2C) bus to initialize configuration of the SAA7113H chip. The SAA7113H video decoder converts analog signals to digital signals that the DM642 can handle. The signals are then moved to a synchronous dynamic random access memory (SDRAM) controller through extended direct memory access (EDMA). The above provide the foundation for the data analysis and processing system. SDRAM and FLASH memory modules can realize seamless connection with the DM642 through the external memory interface (EMIF). The SDRAM is used to store the collected image data and temporary image processing data. FLASH is used to store since the launch of system application. According to the timing requirements, the DM642 chip can read image data from the memory and perform pretreatment operations, such as smoothing noise and edge detection. Then, the coal height information extraction is realized according to a coal detection identification algorithm that is pre-determined based on the lighting information of the geometry information.

Because the existing various coal has not lighting. To obtain a clear image of the coal, active laser imaging technology acquired images are used. The system adopts a pulse laser for long-range real-time lighting to overcome scattered lighting problems due to long distance transmission. Thus, coal can be protection identification in any environment.

The hardware system employs a complex programmable logic device (CPLD, EPM240T100C5 Altera Corporation) and a range gating synchronous control circuit for a SNV (842 w/X laser) ICCD imaging system. Then, a strobe function is realized. The system requires a charge coupled device (CCD) camera with an external trigger function, high spatial resolution, high quantum efficiency, and sufficient dynamic gain range. A normal CCD camera cannot provide sufficiently high resolution images in low light conditions and requires high laser power. Thus, an enhanced ICCD camera is used. ICCD is a type of CCD camera that uses an optical fiber connected to a micro channel plate image intensifier .The ICCD has high light sensitivity and low laser power requirements. The intensifier can increase the gain light detector, magnify weak light signals and has a quick switch function. ICCD performance is superior to ordinary CCD devices under low illumination conditions. The laser imaging principle diagram is shown in Figure 2.

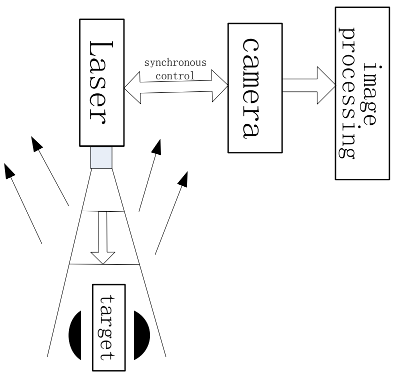


Figure 2. Principle diagram of laser imaging

This system adopts the range gated laser active imaging technology to obtain images. This overcomes the lack of small target detection in a dark environment over a long distance of traditional coal detection systems. It can provide high-resolution images and is not affected by ambient light. Therefore, the system can perform sufficiently without any auxiliary light source environment.

III. IMAGE EDGE DETECTION

A. Image Preprocessing

An image edge contains significant and valuable boundary information. This information has significant influence on subsequent image processing. Coal mining environments are dark and there have high dust and humidity, and the coal testing system device is easily affected by mechanical vibration near working platforms. Therefore, the original images collected in a coal mine have some noise. The noise obscures the characteristics of the image, which introduces major difficulties for edge detection. Eliminating image noise and retaining image details have significant influence on subsequent coal imaging. A mathematical morphology algorithm is first used to filter the original image.

The morphological filtering effect depends on the structural elements and size, as well as the operation methods of transformation. Open morphological operations can remove relatively small structural elements and closed operations can remove small dark details. If joint open and closed operations constitute a composite filter, this can remove positive impulse noise and negative pulse noise in the image simultaneously. To maintain good denoising performance of the morphological transformation, give full play to the noise suppression, and maintain the details of different structural elements, a multielement composite filter is constructed.

Specifically, $B1$ and $B2$ structure elements are alternated between open and closed morphological operations for the original image A.

$$K = \left(A \mathrm{O} B_1\right) \bullet B_2 \tag{1}$$

In Formula (1):

$$B_1 = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \quad B_2 = \begin{bmatrix} & 1 & \\ 1 & 1 & 1 \\ & 1 & \end{bmatrix}$$

Here, $B1$ is a 2 * 2 small scale structure element and $B2$ is a 3 * 3 diamond-shaped structure element. Although the denoising ability of relatively small scale structure element $B1$ is weak, it can maintain image details. Although the large scale structural elements $B2$ will blur image details, it has better ability to remove noise. Thus, by using both filters alternately, the proposed system can retain the image details and filter noise effectively.

B. Edge Extraction

Edges reflect the discontinuity of image pixels. The purpose of image edge detection is to detect the local characteristics that change drastically or discrete pixels. Then, the object boundary is constituted by connecting these pixels. Significant and valuable boundary information is contained in the image edge. This information has significant impact on image analysis and recognition. Thus, edges are widely used in target recognition, computer vision, image segmentation, and region matching, etc. It should be noted that an edge has relative invariance. Changes of light may affect the appearance of a region but not affect the edge. Recently, many studies have examined image edge detection.

For digital image edge detection, an image is usually processed as a whole in the spatial domain or frequency domain for the corresponding processing. Edge detection commonly employs Sobel, Robert, and Prewitt operators. These operators extract edges by maximum gradient detection. The Laplace operator extracts the boundary by detecting the zero crossing point of the second derivative. These operators include various differential operations. Their characteristics are simple and easy to realize. However, the edge detection results are poor due to image noise. Partial edge details are often lost, and the noise is increased. Thus, edge detection is unsatisfactory. In recent years, the Log and Canny edge detection operators have been presented. Although the effect is improved, the amount of required calculation is large and real-time performance is poor. The theory of wavelet transform and mathematical morphology has been introduced to image processing, which has opened new ways to achieve edge detection.

Qiao Naosheng et al. combined the advantages of wavelet transform modulus maxima image edge detection and improved mathematical morphology edge detection. They used a superposition arithmetic fusion image to detect edges. Li Jie et al. proposed an adaptive edge detection algorithm based on mathematical morphology. The image edge is exacted in different direction relative to the sizes of structure elements. Liu Qing et al. combined quantum superposition and information entropy. In their method, a structural element of a quantum superposition structure is constructed. The structural element covers the line of an arbitrary direction and detects a complete continuous edge. The probability of a superposition structural element is determined based on image energy entropy in the algorithm. However, they only consider the energy distribution of the component itself and ignore the energy difference between each component. Thus, they are unable to distinguish between noise and effective image signal according to the entropy value. An empirical mode decomposition is used for edge detection in Zhao Chen's paper, which improved the traditional bidimensional empirical mode decomposition method. The original image is decomposed into intrinsic mode function components on multiple scales and the sum of a margin. Full use is made of the advantages of intrinsic mode function 1 (IMF1) and IMF2 small scale components. Two directional edges are mixed to obtain a result. However, the effect is general, and two-dimensional spatial correlation defects exist.

The concept of mutual information comes from information theory and is an extension of the entropy concept, which describes the amount of information and the statistical dependencies between each piece of information. As the association between two random variables increases, the mutual information also increases. In contrast, the mutual information can become smaller if two random variables are independent. In this case, mutual information will achieve the minimum value of zero.

Aiming to improve the shortcomings of these edge detection methods, an improved noisy image edge detection algorithm is proposed in this paper. The algorithm combines the advantages of BEMD decomposition, mutual information entropy, and image overlay. The mutual information and edge gradient features are effective for integration. First, the image is broken down by BEMD. The strength of association between the high frequency and low frequency is measured by mutual information entropy between adjacent components. If a certain amount of mutual information entropy reaches a predetermined threshold. The component will be the demarcation point between the high frequency and low frequency parts. High frequency components' edges are detected by the wavelet transform modulus maxima method. Edges of the low frequency part are detected by the mathematical morphology method. Finally, the advantages of the two methods are combined, and the images are fused to obtain the image edges.

This method can strip the various modal implied according to its own information characteristics of the image. Image signal filtering can be achieved by image fusion. At the same time, the details of the image edge features are well preserved. The results show that the algorithm combines the efficiency of the edge alignment method and the accuracy of the maximum mutual information method. The details of the original image are better reflected while effectively retaining the image edges.

Empirical mode decomposition (EMD) is a new method of signal time-frequency analysis that was proposed by N.E Huang et al. in 1998. Later, the one-dimensional EMD method was extended to a two-dimensional field to become BEMD which can decompose images into partial narrow-band signals. Due to the potential applications, BEMD has been gradually applied in image fusion, edge detection, image filtering, etc.

Popular signal analysis methods, such as wavelet analysis, are used to analyze time-varying frequency signals. Such methods use integral analysis with Fourier transform as the theoretical basis. The basis functions are fixed and adaptability is limited. In addition, the frequency changes over time cannot be accurately described. Empirical mode decomposition is a new method for nonstationary and nonlinear signal time-frequency analysis. The biggest breakthrough is that this method does not rely on a basis function. It relies on a data-driven adaptive analysis method. The time series signal is decomposed into a set of intrinsic mode functions that contains different scales and basis functions that are not required by the method. Thus, the method has multiresolution and adaptive characteristics.

Specifically, empirical mode decomposition involves a complex signal that is decomposed into the sum of a series of basic intrinsic mode function (IMF) in a time domain. Each IMF must satisfy the following conditions:

(1) The number of extreme value points and the number of passing zeroes must be equal or at most a difference in the data segment.

(2) The envelope line value defined by the local maximum and minimum is zero.

The basic idea of EMD is that the extremum signal is first obtained for a given signal. Then, a signal envelope and its average are obtained by interpolation and the difference between the original data and the average is calculated. Thus, the first signal layer is obtained by decomposition. Until the signal is decomposed into a combination of a finite number of IMFs and the residual function $r_n(t)$, the decomposition process can be expressed as follows.

$$m(t)=\frac{1}{2}\left[u(t)+v(t)\right] \tag{2}$$

$$h_1(t)=x(t)-m(t) \tag{3}$$

$$r_1=x(t)-c_1 \tag{4}$$

$$x(t)=C_1(t)+C_2(t)+\cdots+C_n(t)+r_n(t) \tag{5}$$

In the Formulas, r_n is the residual function and shows the average trend of the signal.

If $r_n(t)$ is ignored in Formula (5), then

$$X(t)=x(t)-\sum_{i=1}^{n-1}C_i(t) \tag{6}$$

In Formula (6), $\sum_{i=1}^{n-1}C_i(t)$ express the sum of the different frequency components of IMF, where $x_{(t)}$ is the original signal. The noise signal is subtracted from the original signal in Formula (5). Thus, the effective signal is extracted.

BEMD first selects the local maximum points and minimum points on the plane for grayscale images. An envelope surface is then formed, and the local average surface is obtained. Then, a finite number of two-dimensional intrinsic mode components and trend items are obtained by continuous screening.

BEMD is data-driven and is thus adaptable in the process of gradually extracting image local high-frequency and high frequency. Thus, the correlation between visual representation and frequency is reflected when people distinguish an image's different textures. Thus, BEMD has a unique advantage in image edge extraction. It can use data-driven features to suppress noise adaptively and effectively when detecting edges. It demonstrates better performance than traditional edge detection algorithms. During the process, the key to effective signal and noise separation is the selection of components for reconstruction. If a refactoring component is selected too frequently and some useful detail features and edge information may be lost. BEMD has components IMF1, IMF2,…, IMFn, and the energy of each IMF is solved as follows.

$$E_i=-\log_2\left(\frac{P_i}{P}\right) \tag{7}$$

In Formula (7): $\sum_{i=1}^{n}P_i=P$. P_i is the energy entropy of the ith signal, E_i is the energy of the ith signal, P is the total energy of all signals, and N is the number of components.

Thus each IMF component that corresponds to natural energy entropy can be expressed as follows.

$$H(x)=E\left[-\lg P(x_i)\right]=-\sum_{i=1}^{N}P(x_i)\lg P(x_i) \tag{8}$$

The correlation of adjacent energy entropy components after BEMD is described using mutual information. The mutual information is expressed as follows:

$$I(X_i,X_{i+1})=H(X_i)+H(X_{i+1})-H(X_iX_{i+1}) \tag{9}$$

In BEMD, an image signal is decomposed in turn from high frequency to low frequency. Formula (5) can be rewritten as follows.

$$x(t)=h_{i,k}(t)+l_{j,k}(t)+r_n(t) \tag{10}$$

In Formula (10), $i=1$, $\cdots$ k and $j=k$, $\cdots$, n . Assume that the mutual statistical of the high and low frequency parts is independent. According to information theory, mutual information between two independent random variables should be zero. Mutual information values between adjacent IMF components will be from large to small to large from high to low frequencies. Then, a turning point is obtained in the process. Thus, by using this feature, the turning point of the high frequency part and the low frequency part is obtained with the principle of mutual information. The objective function is expressed as follows.

$$k=\mathit{first}(\arg\min_{1\le i\le n-1}\left[I(X_i,X_{i+1})\right]) \tag{11}$$

If the high frequency component is discarded directly, its useful information will be lost and the noise reduction effect will be limited. Thus, the edge image f_{Le} can be obtained by the improved gray values in the mathematical morphology of the low-frequency approximate image after dividing. Thus, edge image f_{He} can be obtained. The high frequency detail image f_H can be obtained by the noise-suppressing wavelet modulus maxima method.

In summary, the specific edge extraction process based on BEMD and mutual information is as follows:

(1) Different BIMF components are obtained by BEMD of the noisy source image $f(x,y)$.

(2) The energy entropy of each component is calculated according to Formulas (8) and (9).

(3) Mutual information between the energy entropy components is obtained according to Formula (10).

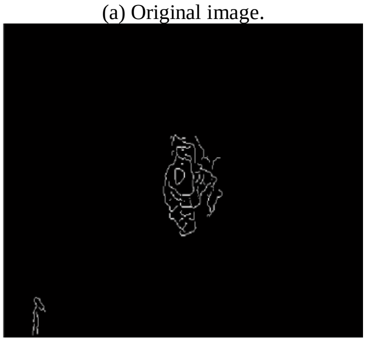
(4) The turning point of the high and low frequency parts is found according to Formula (11).

(5) According to the turning point in step (4), the method of [3] is used to detect edges in a low-frequency approximate image and high frequency detail image. The final result is obtained by fusing the two images.

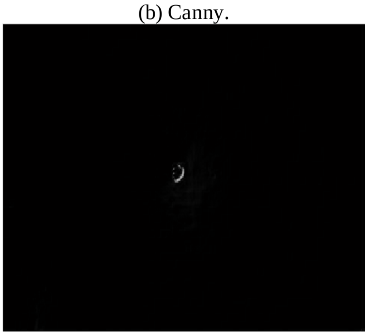
$$f_{He}+f_{Le}=f_e \tag{12}$$

The boundaries of the high frequency and low frequency parts are determined by combing BEMD and mutual information entropy. By comparing the wavelet noise reduction, the selection of a basis function and decomposition layers is not necessary in this method. The noise reduction process is completely adaptive noise reduction that is determined by the signal characteristics. The algorithm combines the efficiency of the edge alignment method and the accuracy of the maximum mutual information method. As is shown in Figure 3, although the edge resolution by the traditional mathematical morphology algorithm detection is higher, the noise suppression effect is not adequate. Compared with traditional method, experimental results show that the proposed edge detection method suppresses noise when image edge details are extracted effectively. Thus, the accuracy of the results is higher, and the proposed method retains more detail information and provides a good foundation for image processing.

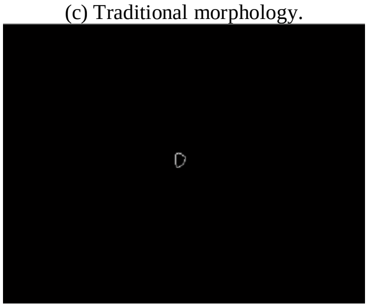
(a) Original image.



(b) Canny.



(c) Traditional morphology.



(d) Proposed method.

Figure 3. Edge images obtained by different methods

IV. GEOMETRIC ALGORITHM

Active laser imaging technology is used to obtain a clear image of coal. The DM642 chip can perform pretreatment operations, such as noise smoothing and edge detection. Then, the coal height information is extracted via a coal height detection algorithm that is predetermined based on the lighting information of the geometry. In the following section, this specific algorithm is explained.

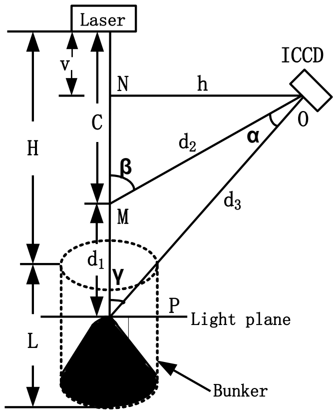


Figure 4. Principle diagram of geometric algorithm

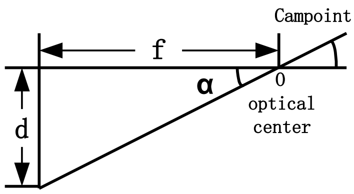


Figure 5. Geometric magnification of ICCD

In Figure 4, H is the distance between the range measurement system and the target coal bunker. L is the coal height. The optical axis of the camera, Z and Y intersect at point M. The optical centre is the point O, its horizontal and vertical distances are h and v, respectively. The geometric magnification of the ICCD is shown in Figure 5. F is the focal length of the camera, d is the distance between the image and the spindle, then

$$\tan\alpha = d/f \tag{13}$$

In the triangle OMP

$$\sin\alpha/d_1 = \sin\gamma/d_2 \tag{14}$$

In Formula (14), $d_2 = MO$. For the system having a certain distance, d_2 is a known constant value. d_1 ($d_1 = MP$) is the distance Y, which is solved by the algorithm. From Figure 4 we can conclude that $\gamma=\beta-\alpha$, then

$$\sin\gamma = \sin\beta\cos\alpha - \cos\beta\sin\alpha \tag{15}$$

Formula (14) can be rewritten as follows:

$$d_1 = d_2 \sin\alpha / (\sin\beta\cos\alpha - \cos\beta\sin\alpha) \quad (16)$$

Then

$$d_1 = (d_2 \csc\beta / f) d / [1 - (\cot\beta / f) / d] \quad (17)$$

If we assume that the camera horizontally scans the lines parallel to the bar alone, then s and t are vertical and horizontal pixel pitch, respectively. The image coordinates of a point (g, d) can be expressed by the sampling number (i, j) ; then, $g = si$ and $d = tj$. Formula (17) can be expressed as follows:

$$d_1 = Aj / (1 - Bj) \quad (18)$$

In Formula (18) $A = d_2 / (t/f)\csc\beta$, $B = (t/f)\cot\beta$; h is the vertical distance between point O and the laser plane.

$$Y = Aj / (1 - Bj) + C \quad (19)$$

Y is the depth of the coal surface glitter. Then, the depth of coal bunker is expressed as follows:

$$D = H + L - [Aj / (1 - Bj) + C] \quad (20)$$

Because the grey values are very different between laser and warehouse in coal. A visible light spot is formed on the interface of the coal seam by a laser beam. The position of the light spot can be accurately extracted from the background by employing an algorithm based on bidimensional empirical mode decomposition and MI. If we assume the initial coordinate of the coal seam image as $(0,0)$, then by Formula (19), the longitudinal distance j between the light spot and initial coordinate of the coal seam image is extracted, and the height of the coal level in the underground bunker can be obtained.

The accuracy results of coal level measurement are shown in Figure 6 by comparing the actual coal depth and the measured values. The accuracy of measurement is gradually improved with an increase in the measurement points, as shown in Figure 6. The experiment result is ideal. Through a series of experiments, the coal level detection system based on the BEMD image-edge extraction algorithm and mutual information is feasible.

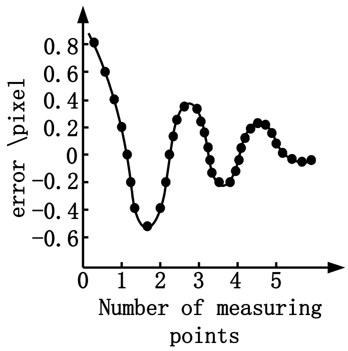


Figure 6. Accuracy results of coal level measurement

V. CONCLUSION

The environments in which coal mining occurs are very complex; thus, there are various methods to image the coal in a bunker. However, there are significant defects that must be overcome when these techniques are applied practically. To date, no single technology can provide long-term, stable and accurate detection of coal level in an underground coal bunker.

An underground bunker coal level measuring system that is based on the DM642 and image processing technology is introduced in this paper. The boundaries of the high frequency and low frequency parts are determined by combing BEMD and mutual information entropy. By comparing the wavelet noise reduction, the selection of a basis function and decomposition layers is not necessary in this method. The noise reduction process is completely adaptive noise reduction that is determined by the signal characteristics. The algorithm combines the efficiency of the edge alignment method and the accuracy of the maximum mutual information method. Moreover, the system adopts the range gated laser active imaging technology to obtain images. This overcomes the lack of small target detection in a dark environment over a long distance of traditional coal detection systems. It can provide high-resolution images and is not affected by ambient light. Therefore, the system can perform sufficiently without any auxiliary light source environment. In conclusion, the system's circuitry is simple, reliable, and provides fast processing. The device does not contact the material and has strong real-time high. So the proposed device shows good application prospects and socioeconomic performance.

REFERENCES

[1] HU Cheng-long. Application of Image Processing Technology in Coal Level Detection. *Coal Technology,* 2011, 30(10), pp. 90-92.

[2] SUN Ji-ping, JIANG Jing. Laser monitoring of the coal level of coal silo by depth pre-calibration. *China Coal Society,* 2012, 37(1), pp. 172-176.

[3] QIAO Naosheng, ZHOU Beiji, DENG Lei. An edge detection method based on image fusion in a noisy image. *Journal of Optoelectronics Laser,* 2012, 11(23), pp. 2215-2220.

[4] XIN Yuan-fang, ZHOU Meng-ran. Research on coal level detecting system of mine coal bunker. *Coal Mine Machinery,* 2013. 05(34), pp. 13-15.

[5] Zhang Ning, Jin Long-xu, Wu Yin-hua, et al. Improved fast SPIHT image compression algorithm for aerial applications. *Journal of Multimedia,* 2011, 6(6), pp. 494-501.

[6] J Iang J A, Chuang Cl, Lu Yl, eta. Mathematical-morphology-based edge detectors for detection of thin edges in low-contrast regions. *IET Image Processing,* 2010, 1(3), pp. 269-277.

[7] Zhao yu–qian, Gui wei–hua, Chen zhen -cheng. Edge detection based on multi-structure elements morphology. The 6th world congression Intelligent Control and Automation, *IEEE Proceedings, Dalian, China,* 2009, pp. 9795-9798.

[8] Norden E. Huang, Zheng Shen, Steven R Long, etal. The empirical mode decomposition and the Hilbert spectrum

for nonlinear and non-stationary time analysis. *Proceedings of the Royal Society of London, Series A, 1998,* 454, pp. 903-995.
[9] ZHANG Xin, SUN Fu-chun. Pulse coupled neural network edge-based algorithm for image text locating. *Tsing-hua Science and Technology,* 2011, 16(1), pp. 22-30.
[10] ZHAO Chen, ZHOU Zhen-guo, CUI Ying. Image edge detection based on two-dimensional EMD improved method. *Journal of Engineering of Heilongjiang University,* 2012, 3(3), pp. 106-110.
[11] Deng L Y, Hung J C, Keh H C, et al. Real-time hand gesture recognition by shape context based matching and cost matrix. *Journal of Networks*, 2011, 6(5), pp. 697-704.
[12] LIU Bo, LIN Yan, WANG Yunlong. Bi-dimensional empirical mode decomposition algorithm for underwater image edge detecting. *Journal of Harbin Institute of Technology,* 2013, 45(2), pp. 117-122.
[13] Wang Nianyi, Ma Yide, Zhan Kun, et al. Multimodal medical image fusion framework based on simplified PCNN in nonsubsampled contourlet transform domain. *Journal of Multimedia*, 2013, 8(3), pp. 270-276.
[14] YANG Feng, ZHANG Jun-ju, XU Hui, et al. Hardware Implementation of an Image Fusion Method. *Infrared Technology,* 2013, 35(9), pp. 541-545.
[15] Ge Weilong, Hua Lianghong, Zhang Xiaohui. Signal to noise research in range-gated underwater laser imaging system. *Infrared and Laser Engineering.* 2013, 42(8), pp. 2022-2026.
[16] Dong Yujie, Jia Xike, Wu Bing. Study on diction of coal level in underground coal bins by irregular light spot images. *China Coal.* 2013, 39(4), pp. 68-70.
[17] Chang Fengyun, Cui Xudong. Design of detection system for non-contact laser level. *Measurement Technique,* 2008(3) pp. 13-15.
[18] Chen Qunying, Song Dongfeng. Measurement method for level of coalfly ash based on nuclear radiation field theory. *China Patent,* 200810017274. 6, 2008-08-20.

Xin Yuanfang (1979-), woman, Anhui Huainan people, Get a master's degree in power electronics and power transmission of Anhui university of science and technology in 2011, lecturer, Mainly engaged in intelligent information processing and image processing aspects of the research.

Jiang Yuanyuan (1982-), woman, Get a master's degree in automation specialty of Anhui university of science and technology in 2006, associate professor, Mainly engaged in pattern recognition and automation specialty of the research.

Liang Zhe (1975-), man, Get a master's degree in automation specialty of Anhui university of science and technology in 2006, associate professor, Mainly engaged in automation specialty of the research.