DPCM Compression for Real-Time Logging While Drilling Data

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***Abstract*—Logging while drilling (LWD) is a drilling technique which obtains and transmits the logging data during oil/gas drilling operations. Because of the limited available transmission bandwidth of mud channel, how to improve the bandwidth utilization becomes a critical problem in LWD research. In this paper, by discussing the information entropy of real logging data, we find that the original encoding of logging data is inefficient. To prune the data redundancy effectively and to improve the bandwidth utilization, we propose a novel compression method on the basis of Differential Pulse Code Modulation (DPCM). To further improve the compression efficiency with less information loss, we introduce the adjustable compression parameters for different kinds of logging data. Extensive experiments with the real logging data show that our method can give enough precise results with the compression ratio of 50% at least. The experiment results also show that our algorithm has the advantages of alterable compressing ratio, excellent decode quality and low algorithm complexity.**

***Index Terms*—logging while drilling; LWD; DPCM; logging data encode;**

I. INTRODUCTION

Logging while drilling (LWD) is a drilling technique, which is used to collect and transmit the information of the formation during oil/gas drilling operations. Different kinds of information, such as density, gamma, resistively and press, are required to be available in real time, because they are important to optimize drilling process, well placement, guide drilling parameter selection and estimation of the oil/gas reserves. However, it is very difficult to transfer the logging data from the bottom to the surface, which makes LWD develop slowly. There are some high-speed transmission technology such as cable, fiber, drill string and electromagnetism, but these transmission technologies are not suitable for practical use because of some technical and economic reasons. Mud-pulse transmission technology, whose positive pulse mode has been available in commercial use, is considered as the most practical logging data transmission technique. However, it has a severe limitation that its transmission rate is no more than 10 bits per second (bps). The limited data transmission bandwidth available with current LWD technology (typical 4 bps) is one of the most challenging problems for real time applications [1]. To solve this problem, researchers exert every effort from different aspects of the LWD system.

Most of the researches focus on increasing data transmission bandwidth [2-6]. They introduced new high-speed transmission technologies (e.g. cable, fiber, drill string and electromagnetism) and tried to make them be suitable for practical use in LWD system. But the fact is that the demand for real-time data is growing much faster than the technology that can practically transfer date increases [1]. So, only enhancing limited transmission bandwidth is not enough to meet the requirement of drilling and we have to maximize the utilization of current limited data transmission bandwidth to satisfy the ever-growing demand for real-time data. Compression provides one solution about maximizing the utilization of limited data transmission bandwidth. Thus, researchers have introduced some compression techniques and information transmission technologies to the LWD realm. Different drilling sensors often provide different amounts of data. All kinds of logging data have to be compressed due to the limited bandwidth of the mud channel. However, most researches on logging data compression mainly pay attention to block data compression, such as image data [1], acoustic waveform data [7] and seismic waveform data [8]). Less work has been done on low rate data compression, such as gamma data, resistivity data, density data and temperature data, which are the basic and necessary measured data in LWD and must be transmitted in real-time mode.

Ref. [9] proposed a lossless data compression method based on the characteristics of logging data, but this method is not suitable for practical use because it takes no consideration to the limitation of the low power consumption and the poor computing capability of logging data collection instruments on the bottom of the wells.

In this paper, we propose a new logging data compression approach, which takes full consideration of the requirement of real-time and the limitation of the low power consumption and the poor calculation ability of drilling devices. The main work and contributions of this paper are as follows. Firstly, we analyze the information entropy of logging information and find that there is redundancy in the logging data, which can be compressed. Secondly, we proposed a novel real-time compression approach. In our approach the Differential Pulse Code

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Modulation (DPCM), which is a lossy compression method, is used to compress the logging data. Thirdly, by analyzing the logging data, we find that the logging data from different instruments has different characteristic. Thus, we optimize the compression parameters for different logging data respectively in terms of their own characteristic to insure the distortion sufferable. Fourthly, extensive experiments are done on the basis of a great deal of real drilling data. Our experiments show that the lossy compression method can give enough precise results when compression ratio is 50%. The experiment results also show that our scheme has the advantages of alterable compressing ratio, excellent decode quality and low algorithm complexity, which indicate its potential for applications. Something should to be noted is that we are cooperating with the instrument manufacturer in manufacturing independent intellectual property instrument based on our proposal.

The rest of this paper is organized as follows. Section II analyzes the information entropy of real logging data and proposes the DPCM-based compression method. Section III performs extensive experiments on the basis of a great deal of logging data from five real drilling wells. Finally, Section IV summarizes this paper with a conclusion.

II. LOGGING DATA COMPRESSION

A. LWD data Information Entropy Analysis

According to information theory, information source X composed of a_i $(i = 1,...,N)$ has information entropy $H(X)$,

$$H(X) = -\sum_{i=0}^{N} p(a_i)\log_2 p(a_i) \tag{1}$$

$p(a_i)$ is the probability of a_i . $H(X)$ actually indicates the minimal code length without information loss under lossless data compression.

This paper analyzes the gamma data and the resistivity data. The similar analyzing approach can be applied to other logging data, such as density, neutron, acoustic, NMR and pressure. The experiments in Section III will be performed on several kinds of logging data, including the gamma, the resistivity, the density, the neutron and the temperature data, which are the common measured data in drilling work.

The electromagnetic wave resistivity sensor (EWR) measures two kinds of resistivity data called SHALLOW and DEEP. The dual gamma ray sensor measures gamma data called DGR. These three kinds of data are represented with 8bits respectively. The existing LWD system does not compress the data by source compression techniques. We calculate the information entropy of the three kinds of data in terms of Equation (2):

$$p(a_i) = c(a_i) / \sum_{j=0}^{N} c(a_j) \tag{2}$$

Where, $N = 255$ and $c(a_i)$ is the count of the times that a_i appears. Taking the values of $p(a_i)$ into Formula (1), we obtain the information entropy of the three kinds of data as shown in Table Ⅰ.

TABLE I. INFORMATION ENTROPY OF LOGGING DATA

Well ID	*No. 1*	*No. 2*	*No. 3*	*No. 4*	*No. 5*
Drilling Time(hour)	24	48	47	22	49
Drilling Depth (meter)	927~ 1893	368~ 1385	254~ 1891	1348~ 1909	380~ 1363
DGR Data Quantity (bit)	14696	41712	39200	16376	44280
Information Entropy of DGR	4.56	4.77	4.815	4.68	4.7
EWR Data Quantity (bit)	29184	82080	75680	31728	86848
Information Entropy of DEEP	6.18	6.24	6.65	6.01	6.18
Information Entropy of SHALLOW	5.92	6.07	6.31	5.86	6.03

Table I shows the information entropy of logging data which come from five different drilling wells. We adopte weighted calculation on data quantity to get the statistical information entropy. The information entropy of DGR is about 4.73 bits, the information entropy of DEEP is about 6.29 bits, and the information entropy of SHALLOW is about 6.01 bits. The results show that the information entropy of each data of the three kinds of drilling measures is less than 8 bits. That is to say, there is redundancy in these logging data, which can be compressed by some compression algorithms.

The existing compression algorithms can be divided into two classes, the lossless compression algorithms and the lossy compression algorithms. The former can recover data without information loss and the latter recovers the compressed data with partial information loss. However, the latter often has higher compression ratio and lower computational complexity than the former.

On one hand, the gamma and resistivity data which are required to be transmitted real-timely and the workers just use them to do qualitative analysis to guide the operation of drilling on the spot, so the real-time performance of the data is much more important than their accuracy. That is to say, a certain data distortion does not have bad influence on data analysis. On the other hand, due to the power limitation of the sensors on the bottom of the wells, low computational complexities of the lossy compression algorithms have to be taken into consideration. Consequently, we select the lossy compression algorithms to enhance the real-time performance of drilling data. In this case, the length of the compressed data will be shorter than the information entropies shown in Table I.

B. Distribution Probability Analysis

To implement the lossy compression algorithm effectively with less information loss as possible as we can, in this subsection, we discuss the probabilities distribution of the three kinds of logging data. Fig. 1 shows the distribution probabilities of DGR, DEEP and SHALLOW. From Fig. 1(a), we can see that the DEEP data is distributed in two intervals, 50~64 and 106~175, and from Fig. 1(b) we can see that the SHALLOW data is distributed in two intervals, 40~64 and 106~160. Fig. 1(c) shows the DGR data is distributed in 25~55. The reason that different kind of measures distributing in different intervals is that the geological characteristics bring on logging data's distribution. That is to say, the same kinds of logging data which are collected from different drilling wells in the same area by the same kind of sensors have the similar distribution. Hence, we can use this conclusion to keep the accuracy of our compressing approach.

Fig. 1(d), (e) and (f) show the first difference of the three kinds of data respectively. The results show that all the first differences of the data are distributed in -5~+5, which means that data change mildly. Fig. 1(d) and (e) indicate that the same kind of data have the similar first difference distribution. Fig. 1(d), (e) and (f) also show that different kinds of data have different first difference distribution. Thus, we use different quantization rules and codebook data to reduce the information loss caused by quantization error of different logging data

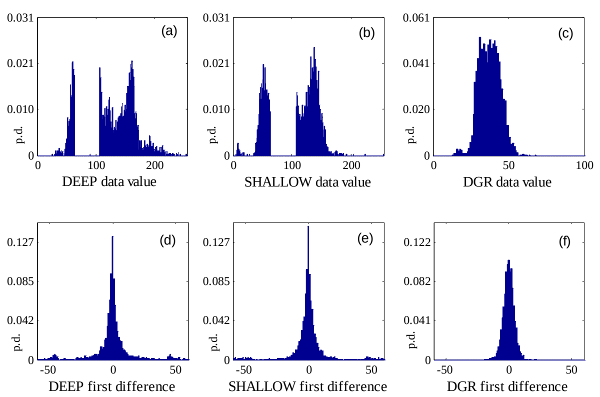


Figure 1. Original data and first difference distribution

Fig. 2 shows the normalized correlation coefficient of DGR, DEEP and SHALLOW. From Fig. 2, all the first-order correlation coefficients of the three kinds of data are higher than 0.98, which mean the logging data have very strong correlation and they belong to the information source with memory.

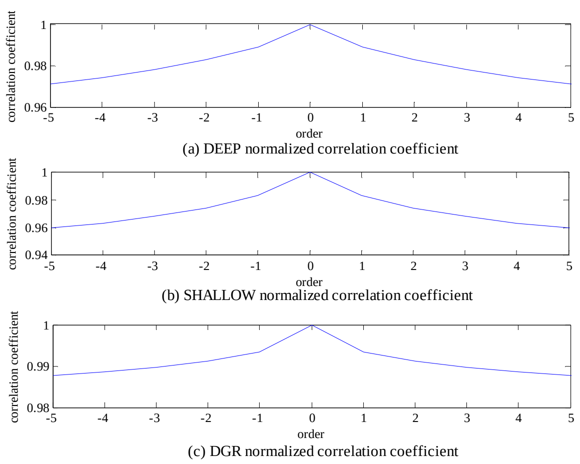


Figure 2. Normalized correlation coefficient

Fig. 1 and Fig. 2 indicate that the logging data have characters of centralized distribution, mild change and strong correlation. The good compression performance can be obtained if we select a lossy compression algorithm which is suitable for the logging data.

C. DPCM-based Compressing Method

As the logging data have strong correlation mentioned above and DPCM is a compression technique which compass data by reducing the correlation among the data, we choose DPCM to perform logging data compression.

Considering the requirements of low complexity, good generality, good maneuverability and low information distortion, we use the first order linear prediction DPCM to compress the logging data.

The steps of our method are as follows:

- 1.Use a predictive function to estimate next data on the basis of existing data;
- 2.Quantify the estimation error between the estimated value and real value;
- 3.Encode the estimation error on the basis of the codebook

DPCM can narrow value range by encoding estimate error value rather than real data value.

For an input sample X_N at time instant N, only data X_J at times $J \le N$ are used in the encoding process to predict $\hat{X}_N$ as the estimated value at time N. e_N is the estimation error and $e_N = X_N - \hat{X}_N$. Quantizer quantify e_N and then get its quantified value e'_N. $q_N = e_N - e'_N$, where q_N is the quantization error caused by the quantizer. The receiver decodes the code and gets its output Y_N in terms of $Y_N = \hat{X}_N + e'_N$. So DPCM error $d_N = X_N - Y_N = X_N - \hat{X}_N - e'_N = e_N - e'_N = q_N$.

The DPCM error is equal to the quantization error and is independent of the receiver. Using the optimal predictive function and quantizer mentioned above, which can be obtained by training set under the condition of minimum mean square error criterion, to compress data can reduce data distortion effectively. In this paper, we select training set with the real logging data which has the distribution similar to encoding data to get the optimal predictive function and quantizer. The training set which has the distribution similar to encoding data is easy to be obtained because exploitation workers often have to drill a large number of wells in the same area to find oil/gas in general. The experiments in this paper use logging data which come from five different drilling wells in the same area.

III. EXPERIMENTS

In order to validate the effectiveness of our method, we implement extensive experiments via using DPCM to encode five real drilling well logging data. The logging data include the DGR data and the EWR data (DEEP & SHALLOW). The drilling depth of the five wells is about

254~1909 meters and the total drilling time is about 190 hours. Moreover, the amount of the total logging data we use is 461,784 bits.

A. Logging Data Preprocessing

To enhance the encoding performance, we have to preprocess logging data with removing singular value and translation transformation at first. Considering the limitation of low power consumption and poor computing capability of the drilling instruments, preprocessing should be simple and have low computational complexity.

Because of the interference caused by the harsh drilling environment [10], sensors may get singular values sometimes. The singular values are useless for drilling work. Moreover, they often enlarge the value range of the correct data, which increases DPCM error and brings down the performances of data coding. So we use the 3σ criterion [11] to detect singular values and replace them with the average value. 3σ criterion is used widely in electronic measurement to remove abnormal data effectively. Supposing $\bar{X}$ is the average of X_i, σ is the standard deviation. If $|X_i - \bar{X}| > 3\sigma$, then X_i is a singular value, replace X_i with $\bar{X}$. To reduce computational complexity, we use formula (3) to get σ.

$$\sigma = \sqrt{\frac{N\sum_{i=1}^{N} X_i^2 - (\sum_{i=1}^{N} X_i)^2}{N^2}} \tag{3}$$

According to formula (3), in order to obtain the standard deviation σ, we only have to do the extraction operation once, do the multiplication operation five times and do the addition operation three times. The computational complexity is constant and does not increase with the growing of data quantity N. So the time complexity is $O(1)$.

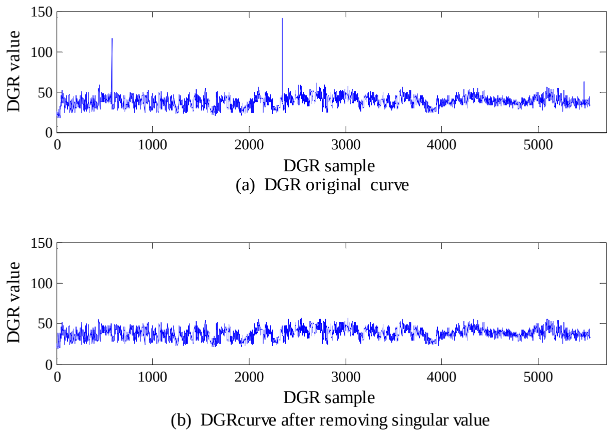


Figure 3. Removing singular value

Figure3 (a) shows the data curves before removing the singular values, which is the original output of sensor. Figure3 (b) shows the data curves that we had removed singular data from normal data. Comparing Figure3 (a) and (b), we find 3σ criterion is effective to remove abnormal logging data. After removing the singular values, the data value range reduce to 20~56 from 18~141.

We find that all five wells' EWR data have no value between 64 and 106. The reason is that the geological characteristics determine the logging data's distributing intervals. Fig. 4 shows the translation transformation of DEEP data. We move the values which are less than 64 to close to 106. Consequently, a narrow value range of logging data is obtained. The receiver recovers the data via the inverse transformation of the values.

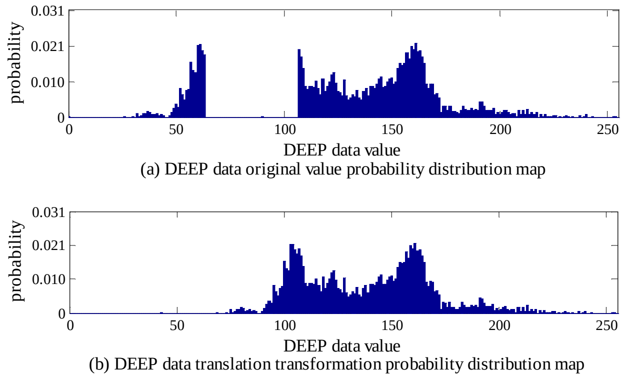


Figure 4. Translation transformation

B. Encoding Experiments

We define the encoding distortion as d to evaluate encoding performance. The encoding distortion d is the ratio of the mean square deviation and the mean value of original data, which is formulated by Equation (4).

$$d = \sum_{i=1}^{N}(X_i - Y_i)^2 / \sum_{i=1}^{N} X_i \tag{4}$$

Where X_i is the value of the i-th original sample and Y_i is the decoded value of the i-th sample.

Table II gives the DGR encoding distortion when using different order predictive function and different code length. The results show that the influence of predictive function order is less than that of the code length. Based on the encoding distortions of Table II, we choose 2 or 3 bits to encode DGR data in practical production. In this paper, the criteria of code length selection are $d < 5\%$. Obviously, one order predictive function and 3-bit length are the best choice to encode the 8-bit original DGR data.

TABLE II DGR LOGGING DATA DISTORTION

Order	DPCM Code Length			
	2bit	***3bit***	***4bit***	***5bit***
1	0.0733	0.0332	0.0125	0.0040
2	0.0651	0.0202	0.0062	0.0024

Table III shows the encoding performance when using one order predictive function and 3 bits to encode the 8-bit original DGR data. The first row of Table III is the well ID of the training data. The first column is the well ID of encoding data. The values of Table III are the values of distortion d. The results show that all the values of d are less than 5%.

TABLE III. DGR ENCODING PERFORMANCE

Encoding	Training Set Well ID				
	No. 1	*No. 2*	*No. 3*	*No. 4*	*No. 5*
No. 1	0.0300	0.0373	0.0351	0.0273	0.0329
No. 2	0.0317	0.0337	0.0337	0.0288	0.0311
No. 3	0.0305	0.0334	0.0341	0.0286	0.0314
No. 4	0.0248	0.0325	0.0309	0.0239	0.0290
No. 5	0.0255	0.0332	0.0329	0.0279	0.0298

Through analyzing Table III, we find that the maximum of d is 0.0373 and the minimum of d is 0.0239, which means different training set has a little influence on DGR encoding performance.

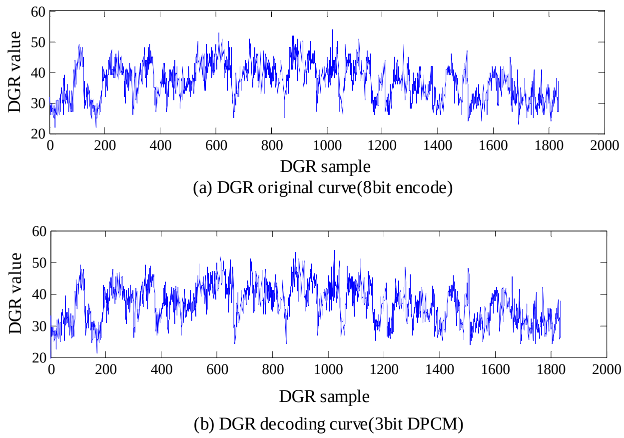


Figure 5. Original DGR curve and decoding curve when d=0.0373

Fig. 5 compares the original DGR data with the DPCM decoded DGR data under $d = 0.0373$, which is the maximum of d in Table III. Something need to be stressed is that d is the maximal can be seen as the worst case. The result shows that the two curves have the same changing trend. That is to say, our method does not disturb LWD user's qualitative analysis even in the worst case when using one order predictive function and 3 bits DPCM to encode the 8-bit original DGR data.

TABLE IV. EWR LOGGING DATA DISTORTION

Type	Order	DPCM Code Length			
		2bit	***3bit***	***4bit***	***5bit***
DEEP	***1***	0.3081	0.0851	0.0274	0.0126
	2	0.2714	0.0798	0.0285	0.0120
SHALLOW	***1***	0.3114	0.1079	0.0314	0.0159
	2	0.2698	0.0727	0.0243	0.0099

Table IV shows the EWR encoding distortion when using different order predictive function and different code length. We can see that the influence of predictive function order is less than that of the code length as same as DGR data encoding. According to the values of d showed in Table IV, we can select 3 or 4 bits to encode the EWR data, i.e., the DEEP data and the SHALLOW data, in practical production. In this paper, we select the one order predictive function and 4 bits to encode 8-bit original DEEP/SHALLOW data.

TABLE V. DEEP ENCODING PERFORMANCE

Encoding Well ID	Training Set Well ID				
	No. 1	*No. 2*	*No. 3*	*No. 4*	*No. 5*
No. 1	0.0470	0.0253	0.0333	0.0323	0.0267
No. 2	0.0726	0.0374	0.0554	0.0487	0.0412
No. 3	0.0848	0.0393	0.0451	0.0448	0.0364
No. 4	0.0903	0.0327	0.0446	0.0444	0.0394
No. 5	0.0368	0.0274	0.0399	0.0323	0.0275

Table V shows the encoding performance when using one order predictive function and 4 bits DPCM to encode the DEEP data. The first row of Table V is the well ID of the training data. The first column is the well ID of encoding data. The values of Table V are the values of distortion d .The maximum of d is 0.0903 and the minimum of d is 0.0253. Compare with Table III, we can state that different training data has greater influence on the encoding performance of the DEEP data than on the DGR data encoding performance. Moreover, the smaller the training set is (for example, the amount of data of well 1 is 29184 bits), the worse the encoding performance is (the maximum of d is 0.0903), and the bigger the training set is (for example, the amount of data of well 5 is 86848 bits), the better the encoding performance is (the maximum of d is 0.0412). So we select large training set, such as the well 2 and well 5, to compute the DEEP data encoding parameter in practical production. In this case, d is less than 5%.

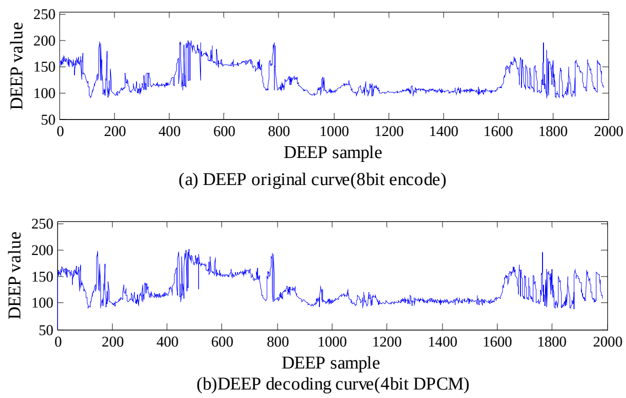


Figure 6. Original DEEP curve and decoding curve when d=0.0903

Fig. 6 compares the original DEEP data with the DPCM decoded DEEP data under $d = 0.0903$, which is the maximum of d in Table V. The result shows that the two curves have the same changing trend. That is to say, our method does not disturb LWD user's qualitative analysis in the worst case when using one order predictive function and 4 bits DPCM to encode the 8-bit original DEEP data.

TABLE VI. SHALLOW ENCODING PERFORMANCE

Encoding Well ID	Training Set Well ID				
	No. 1	*No. 2*	*No. 3*	*No. 4*	*No. 5*

No. 1	0.0206	0.0201	0.0237	0.0214	0.0203
No. 2	0.0254	0.0248	0.0314	0.0295	0.0299
No. 3	0.0291	0.0226	0.0251	0.0273	0.0260
No. 4	0.0536	0.0360	0.0390	0.0328	0.0312
No. 5	0.0226	0.0214	0.0271	0.0258	0.0252

Table VI shows the encoding performance when using one order predictive function and 4 bits to encode original 8-bit SHALLOW data. The first row of Table VI is the well ID of the training data. The first column is the well ID of encoding data. The values of Table VI are the values of distortion d .The maximum of d is 0.0536 and the minimum of d is 0.0201. The result shows that different training data has a little effect on the SHALLOW data encoding performance as same as DGR data encoding. Moreover, Table VI shows most values of d are less than 5%. From the results of the Table VI and the Table V, we can see that the encoding performance of SHALLOW data is better than that of the DEEP data. The reason is that the distribution of SHALLOW data is more centralized than that of the DEEP data as shown in Fig. 1(a) and Fig. 1(b).

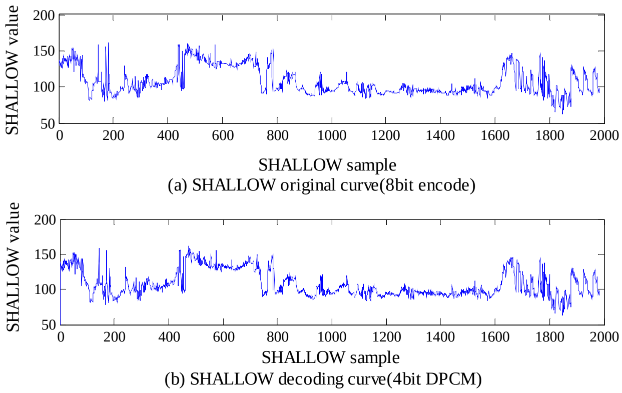


Figure 7. Original SHALLOW curve and decoding curve when d=0.0536

Fig. 7 compares the original SHALLOW data with the DPCM decoded SHALLOW data under $d = 0.0536$, which is the maximum of d in Table VI. The result shows that the two curves have the same changing trend. Thus, our method does not disturb LWD user's qualitative analysis in the worst case when using one order predictive function and 4 bits DPCM to encode original 8-bit SHALLOW data.

C. Other Logging Data Encoding Experiments

The similar analyzing approach can be applied to other logging data, such as density, neutron and temperature. To show the effectiveness of our methods, the other four kinds of logging data are experimented, which include the neutron logging data called NEAR and FAR, the density logging data called DEN and the temperature logging data called TEM. The four kinds of data above are also represented with 8bits in existing LWD systems, respectively. However, no source compression has been performed on them. In following tests, our method is executed on them. Table VII gives the encoding distortion rates about the four kinds of data when using one order predictive function and different code length.

TABLE VII LOGGING DATA DISTORTION

Type	**DPCM Code Length**			
	2bit	***3bit***	***4bit***	***5bit***
DEN	0.1600	0.0548	0.0229	0.0100
NEAR	0.1194	0.0591	0.0194	0.0172
FAR	0.1080	0.0457	0.0172	0.0060
TEM	0.0859	0.0196	0.0147	0.0127

Based on the results of Table VII, we can select 3 or 4 bits to encode the original data in practical production. In this paper, we chose one order predictive function and 3 bits to encode the original density, neutron and temperature data. From Table VII, it can be observed that the distortion is not more than 6%.

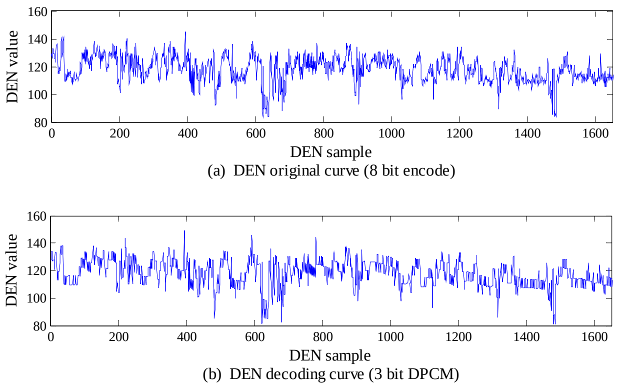


Figure 8. Original DEN curve and decoding curve when d=0.0526

Fig. 8 compares the original density data DEN with the DPCM decoded DEN data under $d = 0.0526$. The result shows that the two curves have the same changing trend.

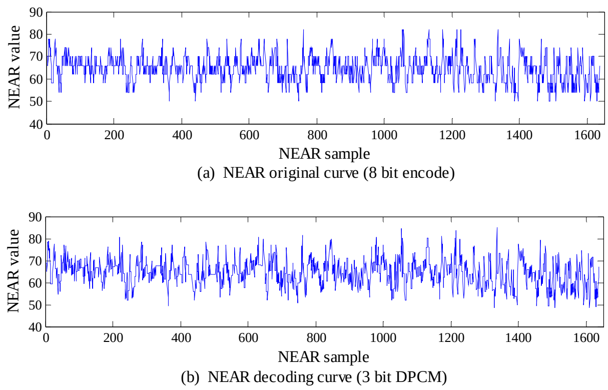
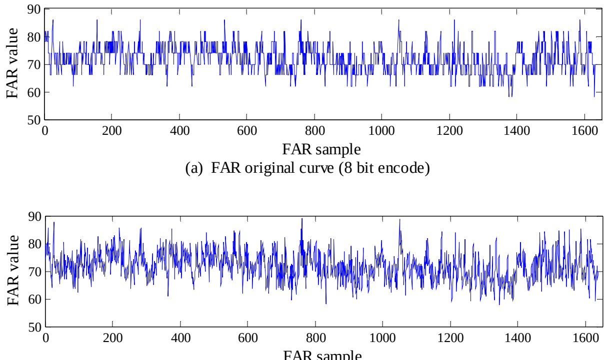


Figure 9. Original NEAR curve and decoding curve when d= 0.0330

Fig. 9 compares the original neutron data NEAR with the DPCM decoded NEAR data under $d = 0.0330$. The result shows that the two curves have the same changing trend.



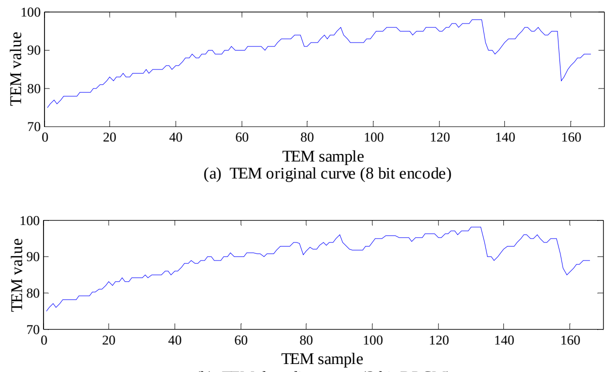
(a) FAR original curve (8 bit encode)

(b) FAR decoding curve (3 bit DPCM)

Figure 10. Original FAR curve and decoding curve when d= 0.0526

Fig. 10 compares the original neutron data FAR with the DPCM decoded FAR data under $d = 0.0526$. The result shows that the two curves have the same changing trend.

Fig. 9 and Fig. 10 compare the original neutron data with the DPCM decoded ones. From the two figures, we can obtain the following conclusions. Like the SHALLOW and DEEP, NEAR and FAR are two kinds of measured data come from the same sensor. Moreover, the encoding performance of NEAR data is better than that of the FAR data, which is just like that the encoding performance of SHALLOW is better than that of the DEEP data. The reason is the value range of the shallow formation measured data (SHALLOW and NEAR is smaller than that of the deep formation measured data (DEEP and FAR), which results in that the distribution of the shallow formation measured data is more centralized than the distribution of the deep formation measured data.



(a) TEM original curve (8 bit encode)

(b) TEM decoding curve (3 bit DPCM)

Figure 11. Original TEM curve and decoding curve when d= 0.0067

Fig. 11 compares the original temperature data TEM with the DPCM decoded TEM data under $d = 0.0067$. The results show that the two curves have the very similar changing trend, and the TEM data has the best encoding performance in all seven kinds of logging data. The reason is that the change of temperature is often very mild, which is very suitable for DPCM.

D. Summarization Of The Experiments

In this section, we use one order predictive function and 3 bits to encode the original gamma, density, neutron and temperature data, one order predictive function and 4bits to encode the original resistivity data. The extensive experiments show that our method can make the results precise enough ($d < 5\%$) with the compression ratio of 50%.

IV. CONCLUSION

In this paper, we proposed a novel real-time compression approach. In our approach the DPCM, which is a lossy compression method, is used to compress the most common logging data (gamma, resistivity, density, neutron and temperature data). To improve the compressing performances, we analyzed the drilling data and found that the logging data from different instruments has different characteristic. So, we optimize the compression parameters for different logging data respectively in terms of their own characteristic to insure the distortion sufferable. Extensive experiments are done on the basis of a great deal of real drilling data. Our experiments show that the lossy compression method can give enough precise results when compression ratio is 50%

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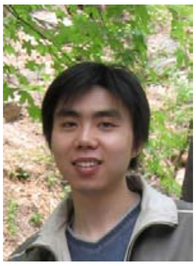

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