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A Generalized Method of Decreasing Data Redundancy

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ABSTRACT In this paper, a method of decreasing the redundancy of information flow by using recurrent properties of Galois code sequences is proposed. For this purpose, the service information is compiled and the priority compression is identified. The method is based on applying one of the adaptive algorithms (prediction first-order, interpolation zero-order, interpolation first-order) by comparing the efficiency of its use when applied to the selected fragments of a signal. It is shown that the developed method is effective for the quick-change signals when the structure and behavior of a signal change drastically. The efficiency of redundancy decreasing at the different sampling rate and the number of the significant samples is evaluated. This makes it possible to establish the limits of the positive effect for redundancy of information flows for the existing and developed methods. Experimental research is carried out for various permissible deviations with obtaining the number of the significant readings. A comparison of the obtained data with results of applying the existing methods in deep pumping installations proved that the proposed method is in 1.3 times more effective than existing ones.

KEYWORDS redundancy decreasing; recurrent code sequences; quasi-stationary flow.

I. INTRODUCTION AND RELATED WORK

IN computer systems, an urgent problem that requires an effective solution for a set of scientific and technical tasks is the maximum reduction of signal redundancy and information flows, with minimal loss of useful information.

In real information systems, the output signals of the analog digital converter (ADC) are formed as a collection of signals of different classes and their periodic sequences [3], accordingly, there is no universal compression method.

Nowadays, many developed methods of information compression have a different scope of application, in particular: photo and video compression [1, 2], solving the classification issues using machine learning and neural networks [6, 9], data compression in wireless sensor networks [7, 8, 10].

In paper [3], the authors made the state of the arts and proposed a rationale for impossibility of creating competitive universal compression algorithms. Moreover, they suggested employing the adaptive methods of redundancy decreasing, and this was mentioned in [23] as well.

Adaptive algorithms for redundancy decreasing are used because modern systems generate a very large amount of data, a part of which is redundant and does not carry any information. They, for example, monitor programs that require continuous data collection in the field of radar signal processing [12,13] or computer systems for medical observation [5, 14].

Most of such data can be efficiently compressed by decreasing the redundancy of information. In particular, in [11], authors proposed methods, in which the difference between the reconstructed and the original signals is guaranteed not to exceed the values defined by the user. Adaptive algorithms with uneven sampling are considered in [4]. In [15, 16], the authors proposed adaptive methods for data sampling with redundancy compression based on probabilistic characteristics. However, this approach may not take into account the structure of input data, which is an important factor for diagnostic signals with quasi-stationary characteristics.

One of the principles of adaptive algorithms for redundancy decreasing is to remove redundant elements by means of information flow approximation. The advantage of these methods is the random selection of the frequency for the process of primary discretization $f(t)$. Here the speed of information flows polling should be selected as a high one, and redundant elements should be removed in a data compressor, which implements the adaptive algorithm.

A polynomial is most often used as an approximating function; that is why, such algorithms for approximation are called polynomial. If an approximating function is the polynomial or with order, which is not more than one, its implementation is the simplest. The efficiency of this class of algorithms for a wide range of data (photo and tele image, service and biomedical information) is comparatively high.

The methods of interpolation and prediction of higher orders, which belong to the class of adaptive polynomial methods of decreasing redundancy with one-parameter adaptation, remain understudied so far.

There are adaptive one-parameter methods to decrease the redundancy of information flows [4, 11]. They discard a part of information from information flows, as it can be restored. However, in these methods, the service information is formed by entering data about the appearance of the significant reading, or the number of the significant reading into the compressed information flow. We consider the service information as information that is generated by the adaptive method, and then it is introduced into the information flow. Such information is necessary for the further correct processing of information flows. The significant reading is the actual reading of the information flow, which is not discarded during the operation of the adaptive method,

As a result, the formed bit sequences have the large-scale redundancy and with a considerable number of significant readings, the efficiency coefficient is less than one.

Adaptive methods for reducing information redundancy in which the algorithm compresses input information in distributed computer systems using recursive code sequences built on the basis of the mathematical apparatus of Galois Fields (GF) [26-28] are promising [17, 18]

The class of such sequences includes recurrent Galois sequences formed over the field GF(2^r), the elements of which form recurrent code sequences.

The symbols of the Galois code sequence are obtained by a cyclic shift of one bit, and the newly obtained value is placed in the lowest free bit. The value that has been in the most significant digit before the shift is added to the encoding sequence becoming its next bit. At the same time, in the vacated position, an element is written that satisfies the recurrence relation:

$$a_{n+i} = -\sum_{j=0}^{n-1} a_{i+j} h_j,$$

where $h_j \in GF(2)$ and $h_0 \neq 0$, $h_n=1$ correspondingly.

The solution to these equations is the sequence a_0, a_1, … . Thus, using the already known k elements of the GF(2) field, it is possible to obtain $k+1$ elements of the same field.

Accordingly, it is necessary to determine the zero-binding of the field GF(2^r) (i.e., the first r symbols), which can be determined arbitrarily and is caused mainly by the specifics of circuit solutions [19, 20, 24].

However, the analysis of the existing methods for redundancy decreasing using Galois code sequences [25] allows us to determine the following functional limitations and shortcomings, namely:

1. The methods are based on predicting a zero order only.
2. These methods cannot be effectively used for quasi-stationary signals as redundancy will increase when they are applied.

In previously published works [21, 22], the polynomial adaptive algorithms for decreasing redundancy were proposed, in which service information was formed using recursive Galois code sequences, mentioned above. In the described algorithms, the real values are replaced by elements of the Galois recurrent sequence. These algorithms are much more effective than the ones considered in [25]. The proposed algorithms are based on predictions of higher orders using the interpolation technique. Each of them demonstrates different efficiency when applied to different types of signals. Therefore, if the input signal is a combination of different types of signals, then the efficiency of using only one method decreases.

According to the analysis carried out in [4], it becomes obvious that to decrease the redundancy of information flows in distributed computer systems, a comprehensive approach to choosing a compression method is required. The use of only one sustainable method of decreasing the redundancy of information flows will not enable to evaluate the structure of the incoming information flow. Moreover, it will lead to a lower coefficient of redundancy decreasing, and to increasing the volume of service information.

Therefore, we propose the complex approach to the selection of the adaptive algorithm for decreasing redundancy, as well as to the effective formation of service information using the properties of Galois code sequences.

As it is shown below such approach enables to select a more effective algorithm of redundancy decreasing and obtain higher compression ratios.

II. PROPOSED METHOD

We propose a generalized method that is based on the combination of three adaptive algorithms [21, 22]. The proposed method, firstly, identifies the input information flow and, secondly, selects the optimal adaptive algorithm for reducing redundancy by comparing the compression coefficients according to binary values.

The basis of the generalized method are three previously developed algorithms for decreasing the information flow redundancy, in particular: (i) algorithm based on prediction of the first order with passing the actual value of a previous reading (Per_1); (ii) algorithm based on interpolation of a zero order (Int_0); (iii) algorithm based on interpolation of the first order with the four degrees of freedom (Int_1_4CC). In each of these algorithms, service information is formed by elements of Galois recurrent code sequences [21, 22]. At the same time each reading is presented as a bit of a sequence, and the indicator of a significant reading is an inverted value of an element of recurrent code sequences.

To predict the first order, the principle of selecting significant readings is based on evaluation of the next reading with the help of the values of two previous readings, whereas a bit recurrent sequence.

With the receipt of the first two actual readings $y_1 y_2$, the inverted element of the recurrent Galois code sequence $\bar{G}_1 \bar{G}_2$ is assigned to every received reading:

$$y_2 \bar{G}_2 y_1 \bar{G}_1.$$

Before receiving the next third actual reading y_3, its predicted value $\tilde{y}_3$ is calculated:

$$\tilde{y}_3 = 2y_1 - y_2.$$

If the predicted value $\tilde{y}_3$ is different from the actual value y_3 by a value which does not exceed the maximum permitted deviation ε,

$$|y_3 - \tilde{y}_3| < \varepsilon,$$

then the Galois code sequence element G_3 is formed:

$$G_3 y_2 \bar{G}_2 y_1 \bar{G}_1.$$

Thus, the real value of the signal is discarded, and an element of the Galois code sequence is transmitted instead.

If it occurs that difference between the actual value and the predicted value is more than the permissible deviation

$$|y_3 - \tilde{y}_3| > \varepsilon,$$

then both the element of the Galois code sequence (in inverted form) and the actual value itself will be transmitted

$$y_3 \bar{G}_3 y_2 \bar{G}_2 y_1 \bar{G}_1.$$

To determine the predicted value of the fourth reading y_4, the actual value of the second reading y_2 and the predicted value of the third reading $\tilde{y}_3$ are used:

$$\tilde{y}_4 = 2y_2 - \tilde{y}_3.$$

To determine the predicted values of the next readings, the predicted values of two previous readings have already been used:

$$\tilde{y}_5 = 2\tilde{y}_3 - \tilde{y}_4.$$

The first reading y_{k+1} is obtained with the interpolation of a zero order. It will be the beginning of an approximating line. The element G_{k+1} of the recurrent code sequence is formed upon the receipt of the signal first value. Then the next reading y_{k+2} is obtained, and the difference between the first reading y_{k+1} and the obtained one y_{k+2} is found. If the difference is not more than the acceptable deviation ε, then the arithmetic mean of this difference is stored, and the element G_{k+2} of the recurrent code sequence is both generated and transferred, and the next reading y_{k+3} is obtained. Then the maximum y_{max} and minimum y_{min} values are found among all the readings between the current and initial y_{k+1} readings. If the difference between them does not exceed the acceptable deviation, then the direct bit of a recurrent code sequence is generated once more and transferred as well. Further, the next value is expected and the procedure is repeated. The maximum and minimum values are found among all the readings obtained starting from y_{k+1} to the current value of the just received reading.

The algorithm of the first order interpolation is based on the constant adjustment of an approximating line. With obtaining the first reading y_{j+1}, which will be the beginning of the approximating line, an inverse bit of the recurrent code sequence $\bar{G}_{j+1}$ is generated and transferred to the receiver with the value of y_{j+1}.

The end of the approximated line is determined in the just received reading y_{j+n}. The obtained approximated line has the limits of the maximum permitted deviation with the width 2ε. It is checked whether all the readings between the first and the last one is within the permitted deviation.

If all the obtained readings are within the formed limits, then the approximating line remains unchanged, and the value of the next reading is received. If the readings are not within the formed limits, then the approximating line is adjusted so that all the received readings are within the permitted deviation.

A sampled and quantized signal is transmitted to the input of a redundancy reduction device. Its values x_i are immediately delivered to all the inputs of compressors, which implement the separate algorithms of redundancy decreasing. Each of compressors forms its bit flow of compressed data, and compression coefficients k_1, k_2 and k_3 are determined per each algorithm correspondingly (Fig. 1).

A maximum coefficient is determined among all the coefficients. Consequently, the bit sequence of compressed data (G G G) with the largest coefficient is delivered to the input of the device along with the algorithm indicator *O* (Fig. 2). For indicator *O* the elements of the recursive Galois sequence can be used as well.

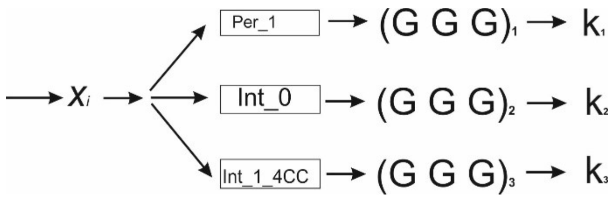

Figure 1. Determination of compression coefficients per each of the algorithms.

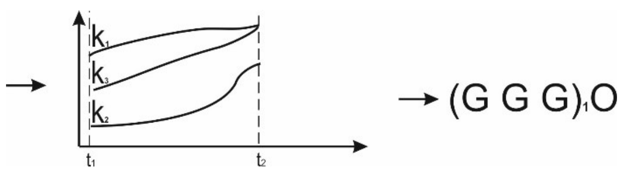

Figure 2. Determination of the optimal algorithm

If, after some time, the coefficient of another algorithm becomes the maximum coefficient while taking the next reading, then another sequence of compressed data with a respective algorithm indicator O of the more effective method will be formed, Fig. 3.

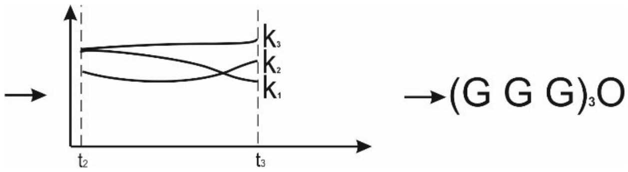

Figure 3. Change of the priority algorithm

Thus, the input information flow will be compressed to maximum by means of forming the information flow different components on intervals of stationary state according to the expression:

$$(G\,G\,G)_i\mathrm{O} = \begin{cases} (G\,G\,G)_1\mathrm{O}, & k_1 > k_2 \wedge k_1 > k_3, \\ (G\,G\,G)_2\mathrm{O}, & k_2 > k_1 \wedge k_2 > k_3, \\ (G\,G\,G)_3\mathrm{O}, & k_3 > k_1 \wedge k_3 > k_2. \end{cases}, \qquad (1)$$

where i – algorithm number, i=1..3.

The expression (1) is a mathematical basis for developing and implementing a specialized processor to decrease the redundancy of quasi-stationary information flows. Quasi-stationary information flow refers to flows that consist of sections with clearly defined patterns. The proposed method selects the most effective redundancy reduction algorithm per each such area (Fig. 4).

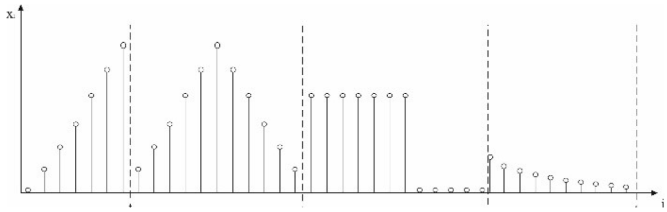

Figure 4. Example of quasi-stationary information flow

Thus, the proposed method of redundancy decreasing is effective when applied to diagnostic signals with quasi-stationary characteristics. The interpolation and prediction methods themselves have the different effectiveness of redundancy decreasing when applied to signals of the different stable forms. Hence, the use of only one stable method of decreasing redundancy when applied to quasi-stationary signals will lead to growing the volume of service information.

The device with implementing the developed generalized method for decreasing the information flow redundancy with quasi-stationary properties (Fig. 5) consists of the following units and links: 1 – system input, 2 – input of instructions and sync pulses, 3 – comparison module, 4 – main storage unit, 5 – redundancy decreasing module, 6 – buffer memory module, 7 – control and synchronization module, 8 – output register, 9 – system output.

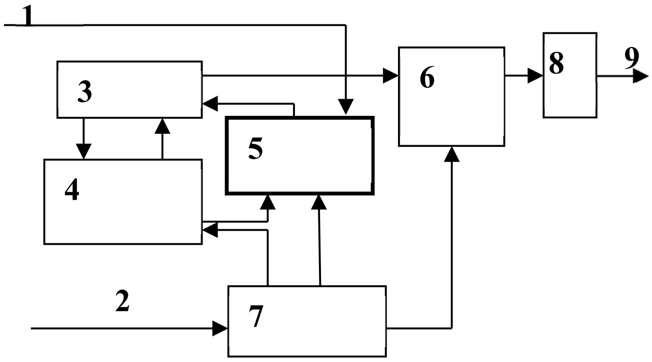

Figure 5. Functional diagram of device for implementing the developed generalized method

Reading values come to the redundancy-decreasing module 5 and to the module 3 where they are compared with a maximum permitted deviation stored in the main storing unit 4. From a buffer memory module 6, readings come at a steady speed to the system output 9. The core component here is the redundancy-decreasing module 5, which operates according to the expression (1).

As a result of the device operation, the incoming information flow is identified and compressed using the most effective of the proposed algorithms. Additionally, a bit compressed flow receives service information of the priority algorithm indicator. For unambiguous identification of the redundancy-decreasing algorithm, two Galois bits (algorithm indicator), are additionally delivered. In this case, the bit sequence will be:

$$g\,g\,y_i\,\overline{G_i}\,G_{i-1}\cdots G_5\,G_4\,G_3\,g\,g\,y_2\,\overline{G_2}\,g\,g\,y_1\,\overline{G_1},$$

where g is a sign of the selected algorithm.

According to the developed method, the input signal will be divided into time intervals (see Fig. 4), each of which provides compression by the most effective algorithm.

Thus, this approach to identifying the structure of input quasi-stationary information message will make it possible to obtain high compression coefficients without exceeding the limits of the maximum permitted deviation when information flow is restored at the receive end.

III. CASE STUDY

The efficiency of the redundancy decreasing method can be determined in two ways. First, it can be run analytically for a mathematical source model; second, it can be done experimentally, using methods of information redundancy decreasing in practice. Some evaluation criteria are discussed in [4, 21, 22,], but each of these criteria do not allow to fully characterize all the features of redundancy decreasing methods.

To compare the algorithms with each other, it is necessary to determine the volumes of formed messages. For this purpose, we have to know a number of significant readings received after the method has been applied. In this case, the efficiency coefficient is as follows:

$$K = \frac{J_0}{J} = \frac{N' \cdot log_2 A}{N \cdot log_2 A} = \frac{N'}{N}, \quad (2)$$

where J_0 – the volume of the input message, J - message volume after applying the redundancy decreasing method, N' – the number of significant readings obtained after applying the redundancy decreasing method, N – the total number of readings, A – the number of quantization levels.

The time synchronization of readings is required to restore the information flow. It is followed by introducing the service information into the information flow. In this case, we mean not just the redundant information, which is introduced during the further compression, but the information only for restoring the initial information flow. That is why, the both compression coefficient and compression efficiency coefficient should be calculated considering service information.

A more accurate evaluation of efficiency can be obtained if consider $J = J_\alpha + J_\beta + J_{cor}$, where J_α - the volume of direct data, J_β – the volume of service information, J_{cor} – the volume of correcting information. In this case, formula (2) will take the form:

$$K = \frac{J_0}{J_\alpha + J_\beta + J_{cor}}. \quad (3)$$

For the developed method, the volume of correcting information will depend on the number of significant readings because two more bits are assigned per each significant reading to identify the algorithm.

Thus, after applying the generalized method, the volume of compressed data is as follows:

$$J_\alpha + J_\beta + J_{cor} = n' \hat{E}[log_2 A] + n + 2n',$$

where n' – the number of significant readings, n – the general number of readings, $\hat{E}[\bullet]$ – the function of rounding to the larger integer.

Then the efficiency coefficient can be determined by the formula:

$$K = \frac{J_0}{J_\alpha + J_\beta + J_{cor}} = \frac{n \cdot \hat{E}[log_2 A]}{n' \cdot \hat{E}[log_2 A] + n + 2 \cdot n'}.$$

Because of service and correcting information, there is a limit of positive compression effect, which will depend on the number of significant readings and frequency of discretization. It has been found out that in order to decrease effectively the redundancy of information flows using the developed method, is necessary to satisfy a condition K>1, i.g. $J_0 > J_\alpha + J_\beta + J_{cor}$:

$$n\ \hat{E}[\log_2 A] > n'\ \hat{E}[\log_2 A] + 2n' + n,$$

and after transformation

$$\frac{n \cdot (\hat{E}[\log_2 A] - 1)}{\hat{E}[\log_2 A] + 2} > n'.$$

Thus, to use effectively the recurrent code sequences, it is necessary to provide that the number of significant readings does not exceed $\left(\frac{(\hat{E}[\log_2 A] - 1)}{\hat{E}[\log_2 A] + 2}\right) \cdot 100\%$ from the general number of readings n.

Table 1 presents the maximum number of readings when the volumes of compressed messages are smaller than the volumes of input data for the 8-bit quantization with different frequencies of discretization.

Table 1. Maximum number of readings with K>1

Discretization frequency	Number of readings	Ratio for maximum number of readings to discretization frequency (in percent)
256	179	70
512	358	70
1024	716	70
2048	1433	70
4096	2867	70
8192	5734	70
16 384	11468	70
32768	22937	70
65536	45875	70

With the presence of two bits of the correcting information, it is necessary to determine the efficiency of applying the generalized method in comparison with the algorithm, which does not use the correcting information. Therefore, it is necessary to satisfy the condition:

$$n' (\hat{E}[log_2 A] + 2) + n < n'' \hat{E}[log_2 A] + n,$$

and after simplification

$$n' (\hat{E}[log_2 A] + 2) < n'' \hat{E}[log_2 A], \quad (4)$$

where n'' – the numbers of significant readings when using just one of three adaptive algorithms, which we call permanent algorithm'.

By converting the expression (4) let us study a ratio

$$n''/n' > (\hat{E}[log_2 A] + 2)/\hat{E}[log_2 A].$$

If we consider the 8-bit quantization, then $\hat{E}[log_2 A]$=8, and

$$n''/n' > 5/4. \quad (5)$$

As it is seen from (5), to satisfy the inequality (4), it is necessary that the ratio between the number of significant readings obtained with the permanent algorithm and the proposed generalized method is not less than 1.25 with 8-bit quantization. In other words, the number of significant readings with the permanent algorithm must exceed the number of significant readings with the generalized method by at least 25 percent.

It is easy to re-calculate the inequality (4) with 16-bit quantization and see that the ratio of significant readings obtained with the permanent algorithm and the proposed generalized method should exceed the value of 1.125.

Thus, the higher the bit rate of quantization, the more effective the generalized method can be. This study does not depend on the criteria of significant reading determination; therefore, the received results are true for arbitrary methods of decreasing the information flow redundancy.

The study of the effectiveness for using the developed method of decreasing the redundancy of information flows when applied to dynamogram signals (specialized signals for diagnosing the technical condition of deep pumping installations for oil extraction from wells) is conducted.

Research is carried out for various permissible deviations, the number of significant readings obtained when applying the developed method is calculated. The obtained data is compared with the results of applying the existing methods in deep pumping installations.

Fig. 6 shows a comparative diagram of the effectiveness for presenting dynamograms by existing methods and the developed method of decreasing the redundancy of information flows for various maximum permissible deviations (2.6%, 4%, 5%, 10%). The maximum permissible deviation is calculated from the amplitude of the dynamograms. Research is carried out for a separate dynamogram on a separate deep installation.

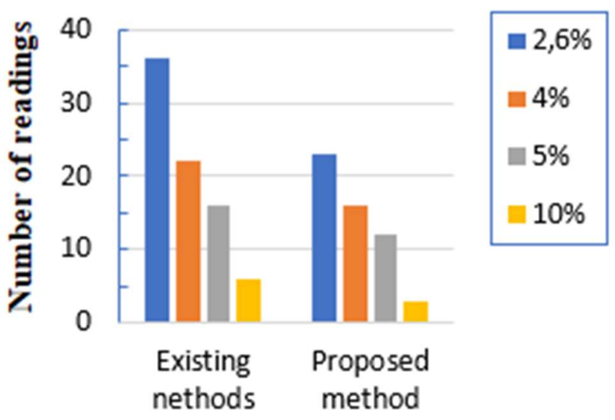

Figure 6. Diagram of effectiveness for decreasing the redundancy of dynamograms

It can be seen in Fig. 6, for example, with 5% of permissible deviations (optimal value for analysis of dynamograms in oil extraction from wells), the proposed method selects 12 significant readings, and the existing ones take 16 readings. This proves that the proposed method is in 1.3 times more effective than existing methods.

IV. CONCLUSION

In this paper, the method of decreasing the redundancy of quasi-stationary information flows is developed, and the analytic expression for adaptive algorithms of data compression by determining a priority algorithm is obtained. That makes it possible to optimize the process of data compression and formulate the basic theoretical foundation for developing the appropriate specialized processors of data compression. It is proofed experimentally that the developed method of decreasing the redundancy is in 1.3 times more effective than existing methods depending on specified values of permissible deviations.

The developed method belongs to the class of adaptive methods of information redundancy reduction and can be used to compress information flows in distributive computer systems, where information flows are formed in real time based on digitalized signals.

In the development of methods for decreasing the information flow redundancy, an important issue is to improve the immunity of compressed data, which are more vulnerable to errors influence in relation to primary information flow.

Therefore, one of the promising directions of the future research is developing the new methods, which ensure the immunity of compressed data generated in the digital form by signals of various forms and types, in the process of their transmission, as well as minimize the redundancy of service information. In addition, an important stage of further research is the influence of noise that are present in real information transmission systems.

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