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Lossless Compression of Telemetry Information using Adaptive Linear Prediction

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1. Introduction

Normal requirement for telemetry data compression algorithms is an ability to recover initial data "as is" without loss of information. This feature is very important in various telemetry processing applications. Precise recovery of the telemetry data as it is acquired from the original source of information is necessary for the analysis of any kind of abnormal events, recovery of bad sites within the telemetry data stream and for other types of post- or real-time data processing [1,2]. The effectiveness of methods of lossless compression is largely determined by the properties of the data under compression [3]. Compression algorithms show better compression ratios if they can adapt to the characteristics of the input data, which are in most cases rapidly change. In this paper we present the results of studies conducted to develop an efficient method of reversible telemetry data compression based on adaptive linear prediction of telemetry data packed according to IRIG-106 format. IRIG-106 is an open standard, developed specifically for aerospace industry, but now used in wide range of telemetry registration applications [4]. Data is packed to frames of fixed length and predefined internal structure. Frame can carry different sources of information: digitized samples of analog signals, as well as pure digital data. For each source a channel of the recording system is provided. The source sample in each channel is introduced by telemetry word. All words in the frame have the same bit width. Telemetry frame contains additional service information in purpose of detecting bit errors, frame synchronization, etc.

Lossless data compression algorithm can be divided into two stages; the first stage - *decorrelation stage*, which exploits the redundancy between the neighboring samples in the data sequence, the second stage - *entropy coding*, which takes advantage from decreasing variance and lowering entropy of the data made on the first stage [5,6,7].

Normally, linear prediction is used for decorrelation stage, i.e. forthcoming data samples can be predicted based on known values of previous data samples, as shown by equation (1).

$$\hat{x}_i = \sum_{j=1}^{p} a_j * x_{i-j} \tag{1}$$

Where $\hat{x}_i$ - the expected value of the current discrete data sample x_i and a=$\{a_1, a_2, \dots \dots, a_p\}$ is the estimated values of the coefficients of the finite impulse response (FIR) filter of order p. At each step i prediction error is calculated by (2).

$$e_i = x_i - Round\ (\hat{x}_i) \tag{2}$$

Where $Round\ (-)$ is the rounding function which produces the nearest integer value to its non-integer input. Filter coefficients are used by the decoder to reconstruct original data samples from the sequence of prediction errors. These filter coefficients are calculated by minimizing the sum of squares of prediction errors and if they are chosen properly, the entropy of e_i should be less than that of x_i .

Efficiency of the decorrelation algorithm can be referenced by two parameters: *filter gain*, which is relation between variance of the source data with respect to variance of the prediction error signal σ_x^2/σ_e^2 , or the *entropy* (which is the smallest average number of bits needed to represent the source output) of the prediction error signal. In practice, efficiency of the algorithm for estimating the entropy is easier to use, since this parameter does not depend on the shape of the source signal [5].

To adapt to changing of non-stationary signals , lossless data systems work on fragmenting data samples into blocks and hence, finding process of these cooeffients becomes increasingly computational expensive with large data block size. So, adaptive FIR filters have been proposed and used successfully for solving such matter [8,9,10].

2. NLMS adaptive filters

An adaptive filter has the property of self-modifying its frequency response to change the behavior in time, allowing the filter to adapt to the characteristics change of the input signal [11,12]. Due to this capability, the overall performance and the construction flexibility, the adaptive filters have been employed in many different applications like linear prediction. Adaptive filter encompass many different classic stochastic gradient algorithms [13].

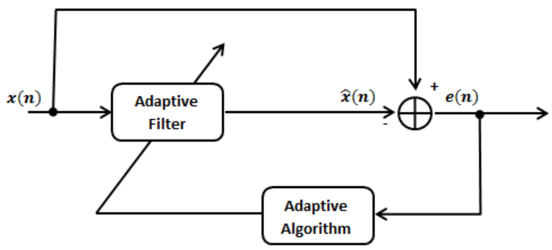


Figure (1). Linear prediction layout using adaptive filter.

One common method is the *Normalized Least Mean Square* (NLMS) algorithm which is suitable for both stationary as well as non-stationary environment and provides a tradeoff between convergence speed and computational complexity [14]. In the case of an NLMS adaptive

FIR filter of prediction order(p)and the set of prediction coefficients $a(n)$= $\{a_1(n), a_2(n), \dots\dots, a_p(n)\}$ is a set of variables varying with time (n). The error of the prediction $e(n)$ of for each sample $x(n)$ is calculated by the expression:

$$e(n) = x(n) - round[a^T(n) * IX(n)] \tag{3}$$

Where $a(n) = [a_1(n)\ a_2(n) \dots\dots\dots\ a_p(n)]^T, IX(n) = [x(n-1)\ x(n-2) \dots\dots\dots\ x(n-p)]^T$ and $[-]^T$ is the transpose operator.

The set of cooeffients $a(n)$ computed iteratively as follows:

$$a(n+1) = a(n) + \mu(n) * e(n) * IX(n) \tag{4}$$

$$\mu(n) = \frac{\mathcal{U}}{\sigma_P^2(n)} \tag{5}$$

$$\sigma_P^2(n) = \beta * \sigma_P^2(n-1) + (1-\beta) * e(n-1)^2 \tag{6}$$

Where, $\mathcal{U}$ - the convergence parameter, β - the smoothing parameter ($0 < \beta < 1$) and σ_P^2 - the input power estimation. For lossless recovery of data samples, original values of $\mathcal{U}$, β, $a(0)$ and $IX(0)$ are added within the compressed data sequence [8,9,10]. In case of adaptive filtering, it is not necessary to fragment data into blocks as it is the case of linear prediction method.

3. Preparing experimental data

Digitized data samples of analog signals, which represent typical telemetry parameters of automatic control system, such as temperature, pressure and positioning information, are obtained in the laboratory. These data then switched into different telemetry frame structures that conform to IRIG-106 standard. The telemetry stream itself is made by the telemetry simulation software described in [15]. But all telemetry parameters are acquired from physical real sources.

Figure (2) shows a timed portion of the acquired data samples and figure (3) shows the histogram of the values of all examined data samples. This graph shows that the values are distributed over the entire range with several peaks.

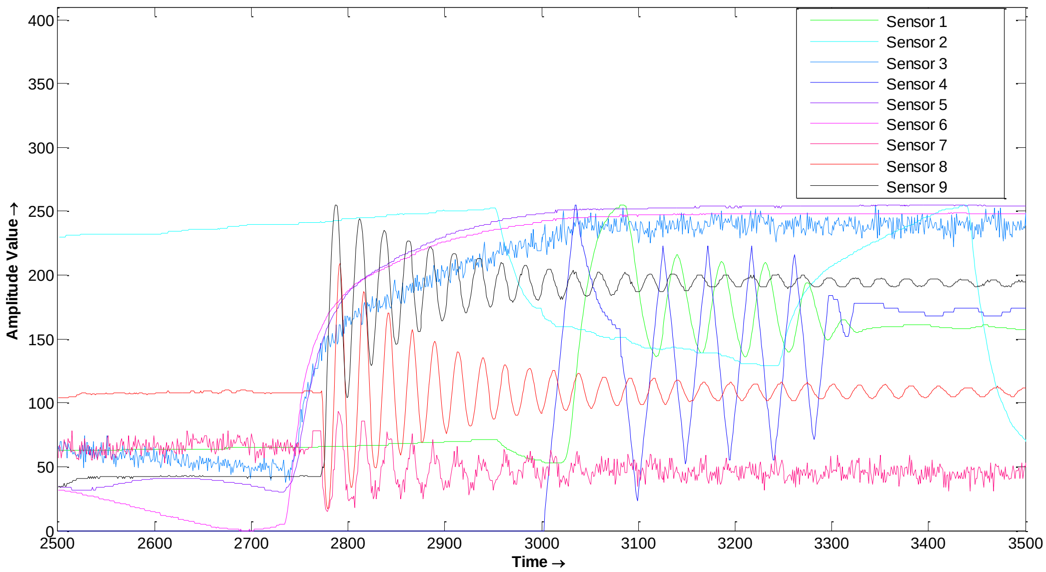


Figure (2). A sample of the acquired data samples.

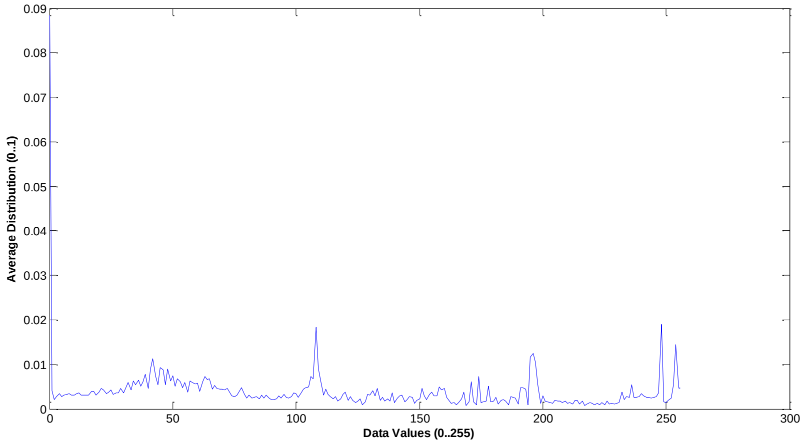


Figure (3). Distribution histogram of values of data words in a stream of telemetry data.

Figures (4) and (5) depict two different types of telemetry frame structures that were used in the experiments (data word length for each of them equals to 8 bits long). *The first type of examined frame structure (Type-A)* – is a telemetry frame structure that consists of nine channels which are connected to the sources of information arranged in one minor frame (major telemetry frame does not contain sub-frame which means one stage of commutation). This frame further also includes additional information that provides frame synchronization in the telemetry stream.

SYNC_F	Data Word: 1	Data Word: 2	Data Word: 3	Data Word: 4	Data Word: 5	Data Word: 6	Data Word: 7	Data Word: 8	Data Word: 9
SYNC16	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5	Sensor 6	Sensor 7	Sensor 8	Sensor 9

Figure (4). Telemetry frame structure without sub-frames (one stage multiplexing), *Type-A*.

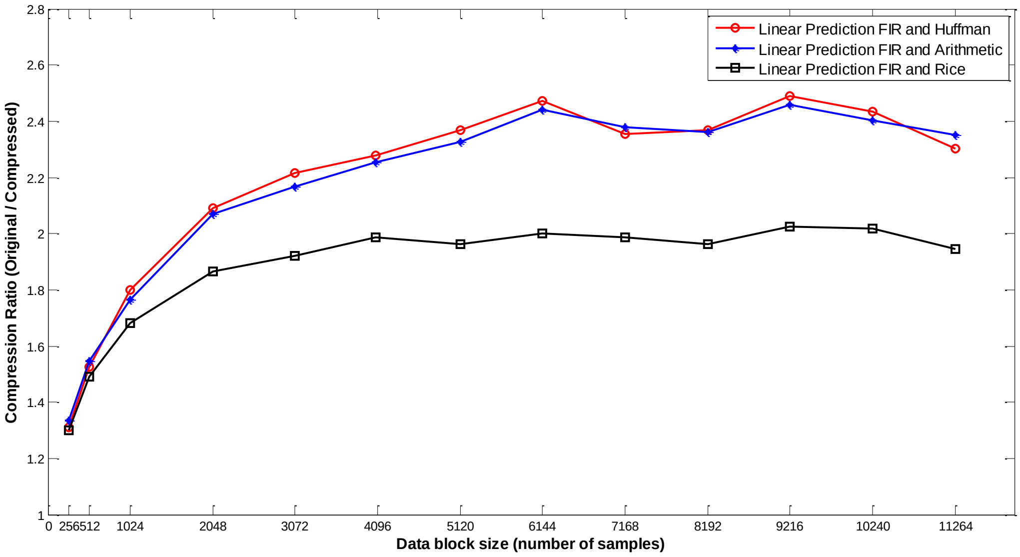
The second type of examined frame structure, Type-B – is a telemetry frame structure that contains a sub-frame, resulting from a two-stage switching circuit. Figure (5) shows a four serial data frame IRIG-106 in which the major frame contains one sub-frame of length four and this sub-frame is attached to the fourth data word. In that fourth channel of the main multiplexer, values are passed to the second multiplexing level. Thus, a complete cycle that reads a complete set of telemetry parameters takes four frames of main multiplexer. During this cycle the main multiplexer channels are sampled four times.

SYNC_F	SYNC_SF1	Data Word: 1	Data Word: 2	Data Word: 3	Data Word: 4	Data Word: 5	Data Word: 6
SYNC16	C1	Sensor 1	Sensor 2	Sensor 3	Sensor 5	Sensor 4	Sensor 7
SYNC16	C2	Sensor 1	Sensor 2	Sensor 3	Sensor 6	Sensor 4	Sensor 7
SYNC16	C3	Sensor 1	Sensor 2	Sensor 3	Sensor 8	Sensor 4	Sensor 7
SYNC16	C4	Sensor 1	Sensor 2	Sensor 3	Sensor 9	Sensor 4	Sensor 7

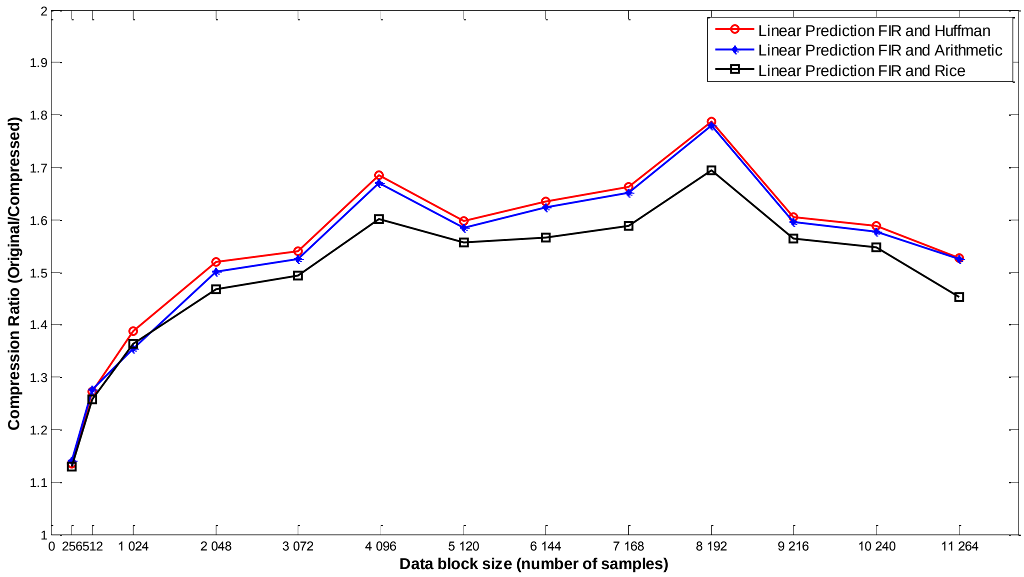
Figure (5) . Telemetry frame structure with a sub-frame (two stage multiplexing), *Type-B*.

For both types of telemetry frame, experiments involve analysis and comparison of implementing a single non-adaptive FIR filter for different block sizes and adaptive NLMS filtering with initially zero coefficients. Decorrelation stage performed by adaptive NLMS filtering is implemented through two different strategies. *First decorrelation method (Strategy-1)* – is by implementing a single linear prediction for the raw stream of the telemetry data and *the second decorrelation method (Strategy-2)* proposed in this paper, is by implementing a separate linear prediction for each data channel based on the structure of the telemetry frame. Compression ratio is used as criterion for assessing the compression algorithm. This parameter is computed as the ratio of the incoming data size to the size of data at the output of the compression system.

Figure (6) shows results of experiments with the single non-adaptive FIR used for linear prediction in conjunction with different entropy coders (Huffman coding [16], Arithmetic coding [17,18,19,20,21] and Rice coding [22]) for *Type-A* and *Type-B* telemetry frame structures with respect to data block size.



a)



b)

Figure (6). Compression performance of linear prediction and different entropy coders with respect to data block size. a) Type-A telemetry frame structure using FIR filter of order (9), b) Type-B telemetry frame structure using FIR filter of order (24).

4. Implementing single NLMS FIR filter for the serial data stream(*Strategy-1*)

Table (1) shows results of applying a single NLMS adaptive FIR on both types of telemetry frame structures (*Type-A* ,*Type-B*) and selecting the best value for smoothing parameter $\mathcal{U}$ which leads to best results of filter gain σ_x^2/σ_e^2 and the entropy of the prediction error signal.

Decorrelation	**Single NLMS FIR filter of order (9).** **(variance of data samples σ_x^2 = 6085,7736 , entropy of data samples = 7,4595)**				
$\mathcal{U}$	0.001	0.01	0.1	0.2	0.9
Filter Gain σ_x^2/σ_e^2	3.6135	11.8452	42.9828	50.9835	44.9741
Entropy of prediction errors	6.9212	4.3352	3.6536	3.7631	4.2909

a)

b)

Decorrelation	**Single NLMS FIR filter of order (24).** **(variance of data samples σ_x^2 = 5967,1569 , entropy of data samples = 7,2611)**				
$\mathcal{U}$	0.001	0.01	0.1	0.3	0.9
Filter Gain σ_x^2/σ_e^2	2.8751	6.7916	18.3531	22.0918	19.0140
Entropy of prediction errors	6.9428	5.4030	4.6006	4.6758	5.0757

Table (1). Performance of single NLMS FIR of order (9). a) *Type-A* telemetry frame structure, b) *Type-B* telemetry frame structure.

The best value of $\mathcal{U}$ is; for *Type-A* telemetry frame structure: $\mathcal{U}$ = (0.1) and for *Type-B* telemetry frame structure $\mathcal{U}$ = (0.3).

Table (2) shows results of the complete two stage lossless compression algorithm that uses adaptive NLMS FIR filter (with initially zero coefficients) combined with different entropy coders for both types of telemetry frame structures. Adaptive NLMS filter produces very close results of compression ratio in comparison with that produced by the non-adaptive FIR filter with no need for data fragmenting.

First stage	**Non-adaptive FIR filter of order (9) and data block size= (6144)**			**A single NLMS FIR filter of order (9) ($\mathcal{U}$ = 0.1, β = 0.9)**		
Second stage	Huffman	Arithmetic.	Rice	Huffman	Arithmetic.	Rice
Compression ratio	2,4719	2,4405	2,0008	2,2239	2,2107	1,9415

a)

First stage	**Non-adaptive FIR filter of order (24) and data block size= (8192)**			**A single NLMS FIR filter of order (24) ($\mathcal{U}$= 0.3, β = 0.9)**		
Second stage	Huffman	Arithmetic.	Rice	Huffman	Arithmetic.	Rice
Compression ratio	1,7872	1,7802	1,6946	1,6872	1,6919	1,6313

b)

Table (2). Compression performance of a single NLMS FIR filter and different entropy coders. a) *Type-A* telemetry frame structure, b) *Type-B* telemetry frame structure.

5.Implementing separate NLMS FIR filter for each data channel(*Strategy-2*)

Table (3) shows results of implementing a separate NLMS adaptive FIR filter on each data channel (nine data channels) for both types of telemetry frame structures and selecting the best value for smoothing parameter $\mathcal{U}$ for initially zero cooeffients.

Decorrelation	**Nine separate NLMS FIR filters, each of order (9) for each data channel (variance of data samples $\sigma_x^2 = 6085{,}7736$, entropy of data samples = 7,4595)**					
$\mathcal{U}$	0.01	0.1	0.2	0.4	0.5	0.9
Filter Gain σ_x^2/σ_e^2	8.7294	32.0928	41.6631	48.9751	49.5996	42.5778
Entropy of prediction errors	3.9844	2.9520	2.8228	2.8203	2.8545	3.0519

a)

Decorrelation	**Nine separate NLMS FIR filters, each of order (9) for each data channel (variance of data samples $\sigma_x^2 = 5967{,}1569$, entropy of data samples = 7,2611)**					
$\mathcal{U}$	0.01	0.1	0.2	0.4	0.5	0.9
Filter Gain σ_x^2/σ_e^2	7.3237	24.3165	30.1311	33.4632	33.5121	28.5575
Entropy of prediction errors	4.2792	3.4387	3.2682	3.2284	3.2641	3.4413

b)

Table (3). Performance of nine separate NLMS FIR filters each of order (9). a) *Type-A* telemetry frame structure, b) *Type-B* telemetry frame structure.

The best value of $\mathcal{U}$ is; for *Type-A* telemetry frame structure $\mathcal{U}$ = (0.4) and for *Type-B* telemetry frame structure: $\mathcal{U}$ = (0.4).

Table (4) shows results of the complete two stage lossless compression that implements single adaptive NLMS FIR filter or separate adaptive NLMS FIR filter for each data channel; with different entropy coders for both types of telemetry frame structures.

First stage	**Nine separate NLMS FIR filters each of order (9) for each data channel ($\mathcal{U}$ = 0.4, β = 0.9)**			**Single NLMS FIR filter of order (9) ($\mathcal{U}$ = 0.1, β = 0.9)**		
Second stage	Huffman	Arithmetic.	Rice	Huffman	Arithmetic.	Rice
Compression ratio	2,818	2,8039	2,1233	2,2239	2,2107	1,9415

a)

First stage	**Nine separate NLMS FIR filters each of order (9) for each data channel ($\mathcal{U}$ = 0.4, β = 0.9)**			**Single NLMS FIR filter of order (24) ($\mathcal{U}$= 0.3, β = 0.9)**		
Second stage	Huffman	Arithmetic.	Rice	Huffman	Arithmetic.	Rice
Compression ratio	2,5472	2,4799	1,9571	1,6872	1,6919	1,6313

b)

Table (4). Compression performance of nine separate NLMS FIR filters; one for each data channel; and different entropy coders. a) *Type-A* telemetry frame structure, b) *Type-B* telemetry frame structure.

Conclusion and work outcome

Experiments under real telemetry data, provides numerical results that allow drawing conclusions about the effectiveness of the proposed methods and developing recommendations for lossless compression of telemetry information. Analysis of the experimentally acquired results leads to the following main results:

-- Compression ratios retrieved from experiments with NLMS FIR filter are very close to that of non-adaptive FIR filter, while NLMS FIR filter shows slightly better results than non-adaptive filter for telemetry data.

-- NLMS FIR filter allows improving performance for (*Strategy-1*), i.e. when telemetry channels are demultiplexed before applying prediction filters. These experiments shows entropy value is about 1.5 times lower at the predictor output in experiments with adaptive algorithm.

-- Huffman method almost in all the experiments shows better compression ratio in comparison with Arithmetic and Rice codes.

-- As expected, results are slightly worse for more complex structure of *Type-B* frame.

Results enlisted, depict an advantage of the approach to lossless telemetry data compression based on adaptive NLMS FIR filter prediction applied at decorrelation stage. The combination of adaptive linear prediction with Huffman source coding is proved to be an effective method for lossless telemetry data compression and is recommended as core algorithm for lossless telemetry compression system. Frame structures with one and two multiplexing levels are examined, which illustrate advantage of the proposed approach for different data packing formats.

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Применение метода адаптивного линейного предсказания для сжатия телеметрической информации

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Эффективность обратимых алгоритмов сжатия во многом определяется тем, насколько точно подобрана модель предсказывающая поведение обрабатываемых данных. Характерной особенностью телеметрической информации является быстрое изменение статистических свойств контролируемых параметров при переключении режимов работы объекта или возникновения аварийных ситуаций. В этих условиях применение адаптивных методов сжатия позволяет существенно улучшить характеристики системы сжатия за счет повышения точности предсказания. В статье приведены результаты исследований метода обратимого сжатия телеметрической информации построенного на основе адаптивного алгоритма линейного предсказания на этапе декорреляции данных. Приводятся результаты исследований эффективности декоррелятора, использующего метод нормализованного наименьшего среднеквадратического отклонения и экспериментальное сравнение нескольких стратегий декорреляции. Определение эффективности работы алгоритмов на этом промежуточном этапе декорреляции производится на основе экспериментально полученных значений дисперсии и энтропии ошибок предсказания. В экспериментах использовались характерные для систем телеизмерений источники данных: параметры систем автоматического управления, записанные в лабораторных условиях, такие как температура, давление и данные позиционирования. Эти данные формируют поток телеметрической информации в соответствии со стандартом IRIG-106, который широко используется в аэро-космической промышленности. Эксперименты проводились с разными видами телеметрических кадров, составленных на основе одно- и двух- ступенчатой системы коммутации каналов. Исследованы комбинации адаптивного предсказателя с различными методами кодирования источника, включая метод Хаффмана, арифметическое кодирование и коды Райса. Проведено сравнение эффективности нескольких комбинаций алгоритмов декорреляции и энтропийного кодирования для сжатия данных телеизмерений.

Получены количественные показатели, позволяющие оценить эффект применения адаптивных методов декорреляции в процедуре сжатия телеметрической информации. На основе полученных экспериментальных данных выработаны рекомендации по разработке системы обратимого сжатия для этого вида информации.

Публикации с ключевыми словами: коммутация, энтропия, телеметрическая информация, декорреляция, обратимое сжатие, кодирование источника, адаптивные методы, арифметическое кодирование, код Хаффмана, код Райса, IRIG-106
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