Preliminary Processing and Lossy Compression of Multichannel Information Data

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Abstract. A task of compressing multichannel information data (MID), i.e., signals from multiple sensors, is considered. Our approach is based on the following distinctive peculiarities: a) representation of multichannel information data as a specific image (2-D data array) and applying lossy DCT-based compression in rectangular shape blocks; b) use of preliminary statistical and correlation analysis for exploiting inter-channel correlation for performing specific pre-processing operations, namely, re-ordering, normalization, cyclic shifting; c) allocation of service data that describe parameters of pre-processing operations into a separate bit-stream and its lossless coding. It is shown that these steps carried out together, can lead to considerable increase of compression ratio for a given fixed measure of distortions (PRD) introduced by lossy compression. The proposed method is tested for simulated data for quantitative evaluation and then verified for real life multichannel signals.

Keywords: multichannel information data, lossy compression.

1 Introduction

Modern industrial control and diagnostic systems are often equipped by a set of sensors that produce simultaneous measurements of certain parameters at given instants of time. Let us give some examples of such systems. One important class is a number of spatially distributed sensors that measure radiation in certain locations around nuclear power stations or other dangerous objects [1]. Another example is a set of sensors that control flight parameters of aircrafts or unmanned aerial vehicles [2]. Modern medical diagnostic systems that register electrocardiograms (ECG) or electroencephalograms (EEG) are also usually multichannel [3,4].

Aforementioned systems and applications might seem having nothing in common since they differ from each other by basic properties of registered signals, sampling rate, number of bits used for each sample representation, etc. However, there are two similar aspects. First, as already said, the obtained (recorded) data in all considered

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systems are multichannel and for some subsets of channels these data can exhibit some degree of correlation. Another unifying aspect is that it is desirable to compress the obtained multichannel data either for transferring them via communication lines or for archiving [5,6].

There exist many different approaches to compression of multichannel information data (signals). First, data can be coded in a lossless or lossy manner [7]. Lossless compression has been a subject of intensive research for several decades but a provided compression ratio (CR) in many practical situations is unable to satisfy user requirements since CR is too small (slightly larger than unity). Due to this, lossy compression techniques have gained popularity in such application areas as audio, telecommunications, telemedicine [6,7], etc. Therefore, below we pay attention to lossy compression of MID.

Second, MID can be compressed component-wise, i.e., separately for each channel. This way is simple but it does not allow exploiting inter-channel correlation that might exist for all or some signals in different channels. Particular solutions already proposed for multichannel ECG and other medical signals have demonstrated that it is worth to exploit inter-channel correlation in one or another manner to improve compression performance [3,4]. Note that inter-channel correlation exists not only for medical MID, but for other types of sensors that register data from a common information source that can be, for example, placed at different distances from particular sensors.

People who dealt with lossy image compression know that such conventional techniques as JPEG and JPEG2000 allow taking advantage of spatial redundancy of data in vertical, horizontal and other directions simultaneously by using data decorrelation [7,8]. Our idea is to exploit this useful property of image coders by representation of MID as a specific image that has much larger amount of "pixels" in rows that correspond to temporal axis of registered (sampled and quantized) data than in columns that correspond to channel indices. MID can be represented as such an image as they are, i.e. column index corresponds to a channel index and no pre-processing is applied. We show that this is not the best way. Channel reordering, signal power normalization in each channel and, possibly, signal cyclic shifting could be operations the use of which results in considerable improvement of data compression performance. The parameters that describe these operations should be either known at decoder side or have to be compressed together with other type of coded data, quantized discrete cosine transform (DCT) coefficients for our variant of MID compression scheme. On one hand, service data on these parameters that form a separate bit-stream occupy some (additional) space. On the other hand, it is shown that in majority of practical situations, this space is very small in comparison to the main bit-stream, and the positive effect of the proposed pre-processing is sufficient.

The influence of the proposed operations on performance of the proposed coder is analyzed by computer simulations for specially synthesized test signals. These signals possess only the most general properties of MID. Particular items like block size and lossless coder selection are discussed as well. At the end, we give some details concerning particular applications of the designed lossy compression scheme and present performance gain.

2 Test Multichannel Signal

In order to simulate basic properties of real life MID, we have created a test multichannel signal. It has been simulated in the following manner. First, a set of mutually independent zero mean i.i.d. random signal $\{A_{kl}\}$ has been generated where l denotes a temporal (row) index and k is a channel (column) index, $l=1,\ldots,L$, $k=1,\ldots,K$. For each k, random values of $\{A_{kl}\}$ had uniform distribution within the limits [-127; 127] and they have been rounded-off to the nearest integer. For the original $\{A_{kl}\}$ the parameters L and K were larger than a required temporal sample size L_s and a number of channels Λ, respectively.

Then, the obtained array $\{A_{kl}\}$ has been subject to a sliding mean filter with a scanning window size NxN with obtaining a new array $\{A^f_{kl}\}$ as $A^f_{kl} = [\sum_{p=l}^{l+N-1} \sum_{q=k}^{k+N-1} A_{pq} / N^2]_{r-o}$ where $l=1,\ldots,L_s$ and $L \geq L_s+N-1$; $k=1,\ldots,K$ and $K \geq \Lambda+N-1$, $[\cdot]_{r-o}$ means rounding-off to the nearest integer. This way one obtains the following properties of the multichannel test signal $\{A^f_{kl}\}$. First, it is an array of 8-bit integers where in a random process in each channel is zero mean and approximately Gaussian (according to the central limit theorem that holds if NxN is large enough). These random processes are characterized by the same (temporal) autocorrelation defined by N and they have approximately equal variances σ^2_k. Inter-channel correlation is also determined by N and the signals in channels with smaller channel indices' difference $|k_1 - k_2|$ have larger correlation factor $R_{k1k2} = \sum_{p=1}^{L} A^f_{k1l} A^f_{k2l} / (L\ \sigma_{k1} \sigma_{k2})$. If $|k_1 - k_2| \geq N$, then $R_{k1k2} \approx 0$. Also note that for $|k_1 - k_2| < N$ the maximal value of cross-correlation function $R_{k1k2}(\Delta l)$ is commonly observed for $\Delta l = 0$. This can be treated as zero mutual shift of channel signals that have some degree of similarity.

All aforementioned properties remain after the next operation defined as $\overset{*}{A}_{kl} = [127 A^f_{kl} / A_{\max}]_{r-o}, A_{\max} = \max_{kl}\{A^f_{kl}\}$ which is intended on "stretching" the simulated data array to the range from -127 to 127. Then the simulated multichannel signal looks like it is shown in Fig. 1 (N=9, Λ=8).

Having the mentioned properties of $\{\overset{*}{A}_{kl}\}$ (in fact, in our simulations $\Lambda = 8$, $L = 4096$), it is easy to simulate different properties of real life multichannel signals. In particular, it is possible to simulate any arbitrary order of one-channel signals in multichannel array and, respectively, an arbitrary set of $\{R_{k\,k+1}, k = 1,\ldots,\Lambda-1\}$. It is also possible to simulate different powers of signals in different channels by multiplying $\{\overset{*}{A}_{kl}, l = 1,\ldots,L\}$ by the corresponding factors F_k for each k-th channel. By cyclic shifting the signals in different channels, one can simulate mutual shifts $\Delta l_{k1k2} \neq 0$, i.e. "delayed" versions of similar signals.

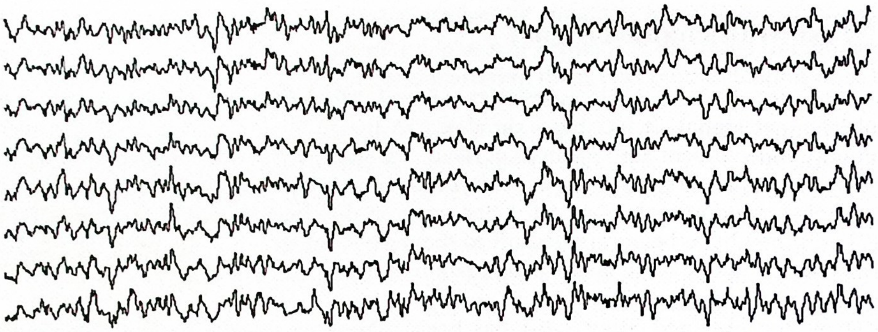


Fig. 1. An example of one realization of the simulated multichannel test signal.

All these effects happen in practice. For example, for standard (Franck) 8-lead system of multichannel ECG the factors R_{k1k2} are commonly of the order from 0.4 to 0.95, powers of channel (lead) signals can differ by several times, and the absolute values Δl_{k1k2} for which maxima of $R_{k1k2}(\Delta l)$ are observed are of the order of tens for sampling rate of hundreds Hz.

For MID that are observed in UAV control, the channel signal properties are essentially different. Considerable (of the order 0.3…0.5) values of R_{k1k2} are observed for few pairs of channels (speed projections, acceleration projections), for other pairs of channel signals that correspond to data of that or of different origin (e.g., altitude and pressure or temperature) the values R_{k1k2}, as can be expected, are practically equal to zero. The values Δl_{k1k2} are equal to zeroes for the channels for which the values R_{k1k2} are large enough. Signal powers in different channels can differ by tens of times since they might correspond to different physical processes and be expressed using particular calibration.

In opposite, radiation MID correspond to signals (sequences of measurements) of the same origin. The values R_{k1k2} for them are commonly larger, Δl_{k1k2} for different pairs of channels can differ from zero, channel signal powers differ a lot.

As seen, the observed phenomena have some degree of similarity (existence of correlation in all or in some pairs of channels), but there are also quite many peculiarities for each particular application. Intuitively, cross-channel correlation should be taken into account in design of MID lossy compression techniques.

3 Proposed Approach to Lossy Compression of MID

As mentioned in Abstract and Introduction, the proposed approach to lossy compression of MID has several distinctive features. The first feature is the use of preliminary statistical and correlation analysis for exploiting inter-channel correlation for performing specific pre-processing operations, namely, re-ordering, normalization and cyclic shifting. The second feature is representation of MID as a specific image and applying lossy DCT-based compression in rectangular shape blocks. The third feature is allocation of service data that describe parameters of pre-processing operations into a separate bit-stream and its lossless coding. Note that in some cases not all operations of pre-processing are to be performed.

Let us consider the proposed approach more in detail. Suppose that for all channels a sampling rate is the same and one has an original MID $\{P_{kl}\}$, k=1,...,Λ, l=1,...,L. A way in which rows of $\{P_{kl}\}$ are assigned to particular signals can be different. For example, sensors can be given by a set of indices and then the k-th row of $\{P_{kl}\}$ corresponds to data from sensor with an index k. If such correspondence is established, let us determine cross-correlation functions $R_{k1k2}(\Delta l), k1=1,...,L-1, k2=k1+1,...,L$ and powers $\sigma_k^2 = \sum_{l=1}^{L}(P_{kl}-\overline{P}_k)^2/(L-1), \overline{P}_k = \sum_{l=1}^{L}P_{kl}/L$ for all k of $\{P_{kl}\}$. Then find the maximal value $R_{k1k2}^{\max}$ of $R_{k1k2}(\Delta l)$ and the corresponding $\Delta l_{k1k2}^{\max}$, also calculate $R_{k1k2} \approx R_{k1k2}^{\max}/\sigma_{k1}\sigma_{k2}$.

Suppose now that there is a correspondence between the set $\{k, k$=1, ...,$\Lambda\}$ and some set $\{m\}$ (this correspondence also defines mappings $\{\sigma_k, k=1,...,\Lambda\} \to \{\sigma_m\}$ and $\{R_{k1k2}\} \to \{R_{m1m2}\}$). The total number of such correspondences is Λ!. Our proposition is to find such reordering of channels that a product $\prod_{m=1}^{\Lambda-1} R_{m\,m+1}$ attains maximal value. In other words, signals in channels of MID are to be placed in such a manner that inter-channel correlation factors for neighbor channels are large.

It might seem that the preliminary operation of channel re-ordering requires a lot of computation. However, in practice it is not always necessary. For example, the values of cross-correlation factors in multichannel ECG do not change considerably depending upon a patient and for several recordings of the same patient. Similarly, for UAV multichannel control data it is possible to establish the "optimal" order of channels in advance. This means the following. After carrying out the corresponding experiments it is possible to recommend some optimal (or, at least, quasi-optimal) order of channel representation of MID in 2-D array (let us denote it as $\{P_{kl}^{opt}\}$. For 8-channel ECG, the optimal order of leads is I-V6-V5-II-V4-V3-V2-V1.

For UAV multichannel data, one has to "group together" the channels that have the same origin and large values of cross-correlation factors, i.e., to place in neighbor channels speed projection data, acceleration data, etc. If the optimal order of channels is fixed and known in advance, there is no need to perform cross-correlation analysis of MID. Moreover, it is supposed known to coder and, respectively, to decoder. Then, no service information on the used order of channels is required. In the opposite case, i.e., if the preliminary operation of channel re-ordering is done, service information dealing with it is the accepted order of channels. It occupies $(\Lambda-1)[\log_2 \Lambda]_\uparrow$ bits where $[\square]_\uparrow$ denotes rounding-off to the nearest larger integer.

Recall that we consider the compression framework that includes Preliminary processing of MID → Performing 2-D DCT in rectangular shape blocks → Quantization of DCT coefficients → Lossless coding of service data and quantized DCT coefficients represented as 1-D array. Within this framework (details will be given below), the use of channel data re-ordering produces CR reduction by 1.03...1.2 times in comparison to the case when optimal ordering is not carried out.

Another operation of preliminary processing is elimination of non-zero Δl_{k1k2}. More in detail, one needs to know $\Delta l_{1k}, k=2,...,\Lambda$ for the selected (used) order of channels in $\{P_{kl}^{opt}\}$. Then, the mutual shift (with respect to the first channel) are to be eliminated by cyclic shifting of data by $\Delta l_{1k}, k=2,...,\Lambda$. The shift values form another subset of service information. Its volume expressed in bits is $(\Lambda-1)[\log_2 \max(\Delta l_{1k}, k=2,...,\Lambda)]\uparrow$. If a channel order is fixed and the values $\Delta l_{1k}, k=2,...,\Lambda$ are stable and known in advance for a given type of MID, the considered operation does not require to perform the cross-correlation analysis of channel data. Also, in this case $\Delta l_{1k}, k=2,...,\Lambda$ can be known at decoder side and there is no need in coded bit-stream of service data.

According to simulations performed for the test signals described in Section 2, the operation of elimination of non-zero Δl_{k1k2} can result in CR reduction (for a given rate of distortions introduced) by 1.02...1.1 times. The benefit is commonly larger when channel signals have a higher degree of cross-correlation and wider main lobes of auto-correlation functions.

The third operation of MID pre-processing is signal power normalization in channels. Here the term "normalization" means that we would like to have (approximately) equal variances $\{\sigma_k^2\}_{norm}$ (or standard deviations) for $\{P_{kl}^{opt}\}$. This can be done in different ways. For example, it is possible to determine $\{\sigma_k, k=1,...,\Lambda\}$ for $\{P_{kl}^{opt}\}$, to find the maximal value $\sigma_{\max}$ among $\{\sigma_k, k=1,...,\Lambda\}$, and to obtain the normalized version of $\{P_{kl}^{opt}\}$ as

$$P_{kl}^{on} = P_{kl}^{opt}\phi_k, l=1,...L;\ \phi_k = \sigma_{\max}/\sigma_k, k=1,...,\Lambda. \quad (1)$$

The set of normalizing factors $\{\phi_k, k=1,...,\Lambda\}$ is one more kind of service data that describe MID pre-processing. This set is subject to lossless compression (coding). Since the values $\{\phi_k, k=1,...,\Lambda\}$ are not integers, their coding might require, at most, 32Λ bits. Note that normalization is a rather simple and fast operation. But it is very efficient in the sense of CR reduction (see next Section).

On the contrary to JPEG, we propose to apply rectangular shape blocks an array $\{P_{kl}^{opt}\}$ is divided to. The block size is ΛL_{bl} where L_{bl} is supposed to be larger than Λ and equal to power of 2 providing faster calculation of DCT in blocks. Rectangular shape of blocks opens several opportunities to scan quantized DCT coefficients while forming a 1-D array subject to lossless coding. We have analyzed the proposed coder efficiency for several variants of scanning and finally decided to apply the modified zigzag scanning illustrated in Fig. 2. We have also tested several different algorithms of lossless coding. The best results have been provided by bzip2 [9].

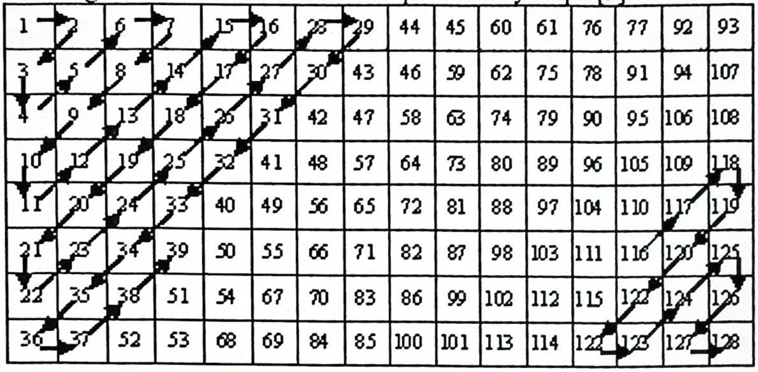


Fig. 2. Quantized DCT coefficients scanning in rectangular block (ΛL_{bl}=8x16)

4 Experimental Result Analysis

Consider now the test signal $\{\overset{*}{A}_{kl}\}$ and its "derivatives". To characterize its compression, let us use a criterion PRD [3, 4] that has been widely exploited in analysis of medical signal lossy coding. For MID, PRD can be expressed as

$$PRD\left(S,S^{dec}\right)=\sqrt{\frac{\sum\limits_{k=1}^{\Lambda}\sum\limits_{l=1}^{L}(S_{kl}-S_{kl}^{dec})^2}{\sum\limits_{k=1}^{\Lambda}\sum\limits_{l=1}^{L}(S_{kl}-\langle S_k\rangle)^2}}\times 100\,. \tag{2}$$

where $\{S_{kl}\}$ and $\{S_{kl}^{dec}\}$ denote the original and decoded MID, respectively; $\langle S_k\rangle$ is the mean in the k-th channel.

Using the test signal $\{\overset{*}{A}_{kl}\}$, we have obtained different signals $\{S_{kl}\}$ and analyzed the dependences *PRD*(*bpp*) (since $\{\overset{*}{A}_{kl}\}$ is an 8-bit data array, CR is strictly connected with *bpp*=8/CR). The procedure of modeling MID with different powers in channels was the following: Case 1 - $S_{kl}=\overset{*}{A}_{kl}, l=1,...,L, k=1,...,\Lambda$ (this case simulates the use of preliminary normalization), Case 2 - $S_{1l}=1.5\overset{*}{A}_{1l}, l=1,...,L$; $S_{kl}=\overset{*}{A}_{kl}, l=1,...,L, k=2,...,\Lambda$; $S_{8l}=2.5\overset{*}{A}_{8l}, l=1,...,L$ (i.e., only in the first and the eighth channels the signal power is larger than in other channels); Case 3 - $S_{1l}=1.5\overset{*}{A}_{1l}$; $S_{2l}=1.7\overset{*}{A}_{2l}$; $S_{3l}=\overset{*}{A}_{3l}$; $S_{4l}=0.5\overset{*}{A}_{4l}$; $S_{5l}=2\overset{*}{A}_{5l}$; $S_{6l}=2.5\overset{*}{A}_{6l}$; $S_{7l}=2.2\overset{*}{A}_{1l}$; $S_{8l}=0.75\overset{*}{A}_{8l}, l=1,...,L$, i.e. in all channels the signal powers are not equal to each other and they differ by several times. The obtained dependences *PDR*(*bpp*) for all three considered Cases are presented in Fig. 3. As seen, the CRs for considerably different signal powers (Case 3) are essentially larger than for the Case of normalized signals (Case 1). Note that the benefit of normalization (degree of CR increasing) is larger than for other operations of pre-processing considered above.

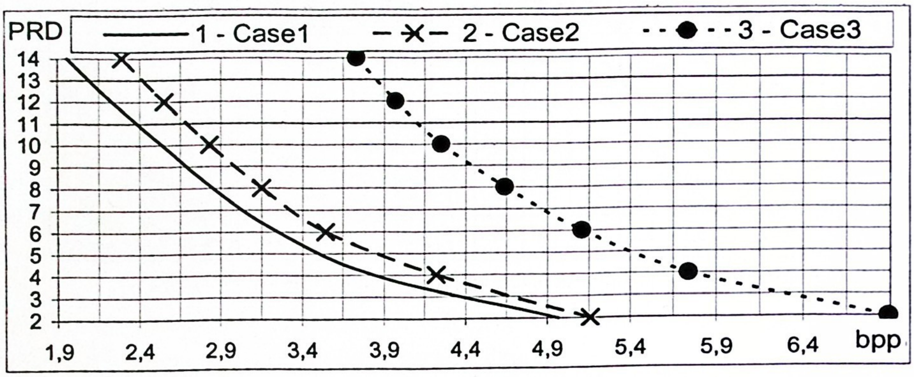


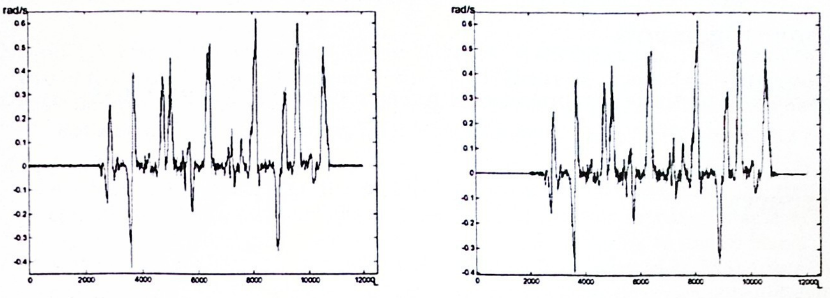
Fig 3. Dependences *PDR*(*bpp*) for MID with different powers in channels.

The CR increasing due to normalization is not the only one benefit of the operation of MID normalization. Our studies have also shown that for the case of normalized MID the PRD values in all channels occur to be approximately equal to each other and equal to the PRD (2). If normalization is not used, PRD values in channels with smaller power occur to be larger than PRD (2), this means that larger distortions are introduced in those channels, and this is undesirable.

We have also tested the influence of block size L_{bl} on CR. It occurred that, in general, L_{bl} increasing leads to larger CR. However, starting from some $L_{bl}^{\min}$ its further increasing does not result in noticeable reduction of bpp. Our recommendation is to select $L_{bl}^{\min}$ by 20...50 times larger than the signal auto-correlation main lobe width expressed in number of samples. For most practical situations $L_{bl}^{\min} = 256$ is enough.

Let us also demonstrate experimental results obtained for real life data. Fig. 4,a presents an original one-channel telemetric signal for testing UAV control system designed by Professor V.I. Kortunov, National Aerospace University, Kharkov, Ukraine (http://k504.xai.edu.ua/eng/nauka_eng.php?link=autocontrol_eng). In aggregate, this system records data for 11 channels, but the plot in Fig. 4,a shows only angular speed data (sampling rate is 50 Hz). The same channel signal after compression (together with other channel UAV data using the proposed method) with PRD=5% and decompression is represented in Fig. 4,b, CR=12. Note that in case of separate compression of data in each channel with the same PRD the obtained CR is 1.3 times smaller. The improvement is provided due to accounting inter-channel correlation.

As seen, no considerable distortions of information are observed; at the same time, noise filtering effect is visible. This is one more positive feature of lossy compression in case of its applying to signals corrupted by noise. Earlier similar effects have been observed in lossy compression of noisy images [10-12].



a b

Fig. 4. Original one-channel signal of UAV control data (a) and the result of its compression and decompression (b)

We have also applied the proposed approach to lossy compression of 8-channel ECG kindly passed to us by the Center XAI-Medica (http://www.xai-medica.com/), National Aerospace University, Kharkov, Ukraine. The reached average (for 9 patients) CR in case of PRD=5% is about 26. This is approximately 1.7 times better than for channel-by-channel lossy compression of the considered ECGs with the same PRD. These results are slightly better than those ones reported in [3,4]. Also note that in case of 12-channel ECG records where there are 4 sum-difference channels it is possible to compress 8 basic channels and to recover sum-difference channel ECGs from the corresponding decompressed channel ECGs. PRD values in sum-difference channels are then about 1.4 times larger than in basic channel ECGs and this is appropriate for practical applications.

5 Conclusions

A new method of lossy compression of multichannel information data is proposed. Peculiar features of the proposed approach consist in applying the operations of preliminary analysis and processing of MID like channel signal re-ordering, normalization and cyclic shifting for improvement of inter-channel correlation of data and, thus, increasing the CR. Another specific feature is the use of MID representation as an image next applying DCT in rectangular shape blocks.

The proposed method has been tested for specially simulated random MID with certain intra and inter-channel correlation properties. It has been shown that the use of all aforementioned operations leads to CR increasing, and the main improvement is contributed by normalization.

Verification for real life MID (UAV control signals and multichannel ECGs) has been performed as well. The obtained results demonstrate that due to incorporating inter-channel correlation of data it is possible to increase CR by 30...70% in comparison to channel-by-channel compression under the same level of introduced distortions. Moreover, these "distortions" may relate to noise removal if original signals subject to compression are noisy.

Acknowledgements

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