A novel efficient encoding engine for CABAC

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1. Idea description

All details related to the proposed approach can be found in this article (see it below).

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In short, in our proposal we have replaced M-coder, which is an encoding engine of CABAC, by our VSW-coder. In our case the reconstructed video for the corresponding quantization parameter (QP) is identical for the original software and the proposed software, so PSNR as well as SSIM values are also identical.

For the given video sequences and QP's set, the proposed VSW-coder provides bitrate savings from 0.22 to 1.03% on average (see Table I) at the same quality and has a comparable computational complexity (see detailed computational complexity analysis in the article below).

Table I. Bit rate savings (in %) depending on QP

	22	27	32	37
Akiyo	0.50	0.85	1.50	2.28
BasketballPass	-0.10	0.07	0.38	0.78
BQMall	0.09	0.12	0.33	0.67
City	0.44	0.46	0.69	1.25
ElFuente	0.10	0.37	0.83	1.32
hall	0.45	0.57	1.08	1.68
Kimono1	0.16	0.20	0.43	0.90
MobileCalendar	0.68	0.70	0.93	1.51
ParkScene	0.21	0.16	0.43	1.03
PartyScene	-0.01	-0.06	-0.05	0.06
PeopleOnStreet	0.21	0.19	0.22	0.33
RaceHorses	0.23	0.28	0.35	0.45
silent	-0.11	-0.01	0.50	1.09
Average	**0.22**	**0.30**	**0.59**	**1.03**

2. Archive file description

The archive file includes original (folder *HM-12.0-org*) and proposed software (folder *HM-12.0-vsw*) which we have used in our experiments as well as frame-by-frame results for each video and QP (folder *results*). Taking into account that in latest versions of HM software the encoding decisions is depend on encoding engine, we have modified the original and the proposed software to have the same input for both encoders by setting of m_entropyBits array to zero values in file ContexModel.cpp

An efficient adaptive binary arithmetic coder with low memory requirement

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***Abstract*—In this paper we propose a novel efficient adaptive binary arithmetic coder which is multiplication-free and requires no look-up tables. To achieve this, we combine the probability estimation based on a virtual sliding window with the approximation of multiplication and the use of simple operations to calculate the next approximation after the encoding of each binary symbol. We show that in comparison with the M-coder the proposed algorithm provides comparable computational complexity, less memory footprint and bitrate savings from 0.5 to 2.3% on average for H.264/AVC standard and from 0.6 to 3.6% on average for HEVC standard.**

***Index Terms*—arithmetic coding, H.264/AVC, HEVC, M-coder.**

I. Introduction

Adaptive binary arithmetic coding (ABAC) is an essential component in most common image and video compression standards and several non standardized codecs such as JPEG [1], JPEG2000 [2], H.264/AVC [3], HEVC [4] and Dirac [5]. Arithmetic coders implemented in these codecs are based on the so called Q-coder [6] which is a multiplication-free adaptive binary arithmetic coder with a bit renormalization and look-up tables used for multiplication approximation and probability estimation.

The most efficient ABAC implementation is the M-coder [7], which is the core of the Context-adaptive binary arithmetic coding (CABAC) used in the H.264/AVC standard. The emerging HEVC standard [4], [9] also uses the M-coder as an encoding engine in CABAC, but in contrast with H.264/AVC the context-modeling in HEVC is significantly simplified. Therefore, the computation complexity and memory consumption portions of the M-coder in CABAC of HEVC are higher than those in H.264/AVC.

Since the M-coder is a key component of the entropy encoding in both compression schemes, the implementation of ABAC with a smaller memory footprint, a lower computation complexity and a higher compression efficiency remains an important challenge.

There exist several approaches to improve the compression efficiency of ABAC; however, all of them require either a multiplication operation in the interval division part, or consume additional memory. In H.264/AVC and HEVC standards, CABAC first divides the input data into several non-stationary binary sources using context modeling. Next, each binary source is compressed by an M-coder which estimates the probabilities using one state machine for binary sources with different statistical properties. However, from a compression efficiency point of view, it is better to find the trade-off between adaptation speed and precision of the probability estimation for each binary source. This task can be solved by utilizing several state machines with different adaptation speeds and precision of probability estimation [5], which unfortunately leads to an increase in memory consumption for storing different look-up tables. Another solution uses look-up table-free approach based on virtual sliding window [10] (VSW). In this approach, the probability estimation is calculated using a simple rule with one parameter – window length, and a trade-off is reached by assigning a specific window length selected according to the statistical properties of the corresponding binary source. The main disadvantage of this approach is that a multiplication operation is required. Improving of compression efficiency can be also achieved by modification of the context modeling in CABAC [11], [12], [13] but it also accompanied by significant increase of computation complexity.

Decreasing the computational complexity can be achieved by modifying the renormalization procedure. In [14], a faster renormalization method is proposed, but it is based on additional look-up tables. As an alternative to arithmetic coders, *range coders* use bytes as output bit stream element and do byte renormalization at a time [15], [16], [17], [18]. In [19] it was shown that adaptive binary range coder allows to decrease computation complexity. However, range coder is not efficient for compression of small length binary sequences and it also uses a multiplication in the interval division part of ABAC, so it is not suitable for hardware applications. Additional interesting direction of the computation complexity decrease can be based on development of a CABAC with a parallelism in data processing [20], [21].

Decreasing memory consumption of CABAC is also a very important issue, especially for hardware implementation. That is why a number of proposals for HEVC standard aim at minimizing memory consumption. In [22] the new CABAC architecture was proposed. This architecture reduces the memory requirement by 67%, but at the expense of 0.25–6.84% coding loss. In [23] a reduction of initialization tables for CABAC contexts lead to coding losses up to 0.4%. In [24] the LPS range look-up table size was reduced by 34% without any degradation of the compression efficiency. To reduce the

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chip area for hardware implementations in [25], the authors proposed to remove look-up tables, but had to introduce multiplications.

In this paper, we present an efficient adaptive binary arithmetic coder. The main contributions of the paper are the following:

1) A new adaptive binary arithmetic coder is proposed which, in contrast with the previous coders, does not use multiplications nor any look-up tables[1].
2) We evaluated the proposed coder's performance and show that it allows allows to easily control the trade-off between the speed of probability adaptation and the precision of probability estimation through a single parameter, the window length. For software applications we show that the proposed coder has comparable computation complexity with M-coder.
3) Two application scenarios for the proposed coder are investigated. In the first scenario, in comparison to the M-coder the proposed coder provides bitrate savings from 0.5 to 2.3% for H.264/AVC standard and 0.6–3.6% for HEVC standard. In the second scenario, a compression improvement of 0.3% in comparison to the first scenario is achieved.

The rest of the paper is organized as follows. Section II reviews the integer implementation of binary arithmetic coding. Section III is dedicated to the look-up table-free probability estimation of ones for a binary source. Section IV describes the state-of-the-art adaptive binary arithmetic encoder implementations. Section V introduces the proposed multiplication-free and look-up table-free adaptive binary arithmetic coder. Section VI evaluates the performance of the proposed coder and M-coder using three main features: coding redundancy, speed of probability adaptation and computation complexity. Two scenarios of usage of the proposed coder and comparative results with the M-coder are presented in Section VII. Conclusions are drawn in Section VIII.

II. Integer implementation of binary arithmetic coding

Let us consider a stationary discrete memoryless binary source with p denoting the probability of ones. In a binary arithmetic encoding codeword for a binary sequence $\mathbf{x}^N = \{x_1, x_2, ..., x_N\}$, $x_t \in \{0,1\}$ is represented as $\lceil -\log_2 P(\mathbf{x}^N) + 1 \rceil$ bits of a number

$$Q(\mathbf{x}^N) + P(\mathbf{x}^N)/2, \tag{1}$$

where $P(\mathbf{x}^N)$ and $Q(\mathbf{x}^N)$ are the probability and the cumulative probability of a sequence $\mathbf{x}^N$, respectively, which can be calculated by the recurrent relations:
If $x_t = 0$, then

$$\begin{cases} Q(\mathbf{x}^t) \leftarrow Q(\mathbf{x}^{t-1}) \\ P(\mathbf{x}^t) \leftarrow P(\mathbf{x}^{t-1})(1-p), \end{cases} \tag{2}$$

if $x_t = 1$, then

$$\begin{cases} Q(\mathbf{x}^t) \leftarrow Q(\mathbf{x}^{t-1}) + P(\mathbf{x}^{t-1})(1-p) \\ P(\mathbf{x}^t) \leftarrow P(\mathbf{x}^{t-1})p. \end{cases} \tag{3}$$

In this paper we use "$\leftarrow$" as the assignment operation, "$\ll$" and "$\gg$" as left and right arithmetic shift, and "!" as bitwise NOT operation.

An integer implementation of an arithmetic encoder is based on two registers: L and R size of b bits (see Algorithm 1). Register L corresponds to $Q(\mathbf{x}^N)$ and register R corresponds to $P(\mathbf{x}^N)$. The precision required to represent registers L and R grows with the increase of N. In order to decrease the coding latency and avoid registers underflow, the *renormalization* procedure [27] is used for each output symbol (see Algorithm 2).

Algorithm 1 : Binary symbol x_t encoding procedure

```
1: $T \leftarrow R \times p$
2: $T \leftarrow \max(1, T)$
3: $R \leftarrow R - T$
4: if $x_t = 1$ then
5:     $L \leftarrow L + R$
6:     $R \leftarrow T$
7: end if
8: call Renormalization procedure
```

Algorithm 2 : Renormalization procedure

```
1: while $R < 2^{b-2}$ do
2:     if $L \geq 2^{b-1}$ then
3:         $bits\_plus\_follow(1)$
4:         $L \leftarrow L - 2^{b-1}$
5:     else if $L < 2^{b-2}$ then
6:         $bits\_plus\_follow(0)$
7:     else
8:         $bits\_to\_follow \leftarrow bits\_to\_follow + 1$
9:         $L \leftarrow L - 2^{b-2}$
10:    end if
11:    $L \leftarrow L \ll 1$
12:    $R \leftarrow R \ll 1$
13: end while
```

III. Probability estimation

In real applications the probability of ones is unknown. In this case for an input binary symbol x_t the probability estimation of ones $\hat{p}_t$ is calculated and used in line 1 of Algorithm 1 instead of p. One of the well known probability estimation algorithms is based on a *sliding window* concept. The probability of a source symbol is estimated by analyzing the content of a special buffer [28]. This buffer keeps W previously encoded symbols, where W is the length of the buffer. After the encoding of each symbol the buffer's content is shifted by one position, a new symbol is written to the free cell and the earliest symbol in the buffer is erased.

[1]This result was briefly presented by the authors in [26]

For the binary sources, the probability of ones is estimated by the Krichevsky-Trofimov formula [29]:

$$\hat{p}_{t+1} = \frac{s_t + 0.5}{W + 1}, \tag{4}$$

where s_t is the number of ones in the window before encoding the symbol with the index t.

The advantage of using a sliding window is the possibility of a more accurate evaluation of the source statistics and a fast adaptation to changing statistics. However, the window has to be stored in the encoder and the decoder memory, which is a serious drawback of this algorithm. To avoid this, the *Imaginary Sliding Window* technique (ISW) was proposed [28]. The ISW technique does not require storing the content of the window, and instead, it estimates symbols count from the source alphabet stored in the window.

Let us consider the ISW method for a binary source. Define $x_t \in \{0, 1\}$ as a source input symbol with index t, $y_t \in \{0, 1\}$ as a symbol deleted from the window after adding x_t. Suppose at every time instant a symbol in a random position is erased from the window instead of the last one. Then the number of ones in the window is recalculated by the following recurrent randomized procedure.

Step 1. Delete a random symbol from the window

$$s_{t+1} \leftarrow s_t - y_t, \tag{5}$$

where y_t is a random value generated with probabilities

$$\begin{cases} Pr\{y_t = 1\} = \dfrac{s_t}{W}, \\ Pr\{y_t = 0\} = 1 - \dfrac{s_t}{W}. \end{cases} \tag{6}$$

Step 2. Add a new symbol from the source

$$s_{t+1} \leftarrow s_{t+1} + x_t. \tag{7}$$

For the implementation of the ISW algorithm, a random variable must be generated. This random variable should take the same values at the corresponding steps of the encoder and the decoder. However, there is a way to avoid generating a random variable [10]. At step 1 of the algorithm let us replace a random value y_t with its probabilistic average. Then the rule for recalculating the number of ones after encoding of each symbol x_t can be presented in two steps.

Step 1. Delete an average number of ones from the window

$$s_{t+1} \leftarrow s_t - \frac{s_t}{W}. \tag{8}$$

Step 2. Add a new symbol from the source

$$s_{t+1} \leftarrow s_{t+1} + x_t. \tag{9}$$

By combining (8) and (9), the final rule for recalculating the number of ones can be given as follows:

$$s_{t+1} = \left(1 - \frac{1}{W}\right) \cdot s_t + x_t. \tag{10}$$

Equation (10) corresponds to the following probability estimation rule:

$$p_{t+1} = \left(1 - \frac{1}{W}\right) \cdot p_t + \frac{1}{W} x_t. \tag{11}$$

IV. State-of-the-art adaptive binary arithmetic coder implementations

A. Multiplication-free implementation based on state machine

One way for implementation of probability estimation can be based on the *state machine* approach. Each state of this machine corresponds to some probability value. Transition from state to state is defined by the value of the input symbol. This approach does not require multiplications or divisions for probability calculation. In addition, the fixed set of states allows to implement the interval division part of the arithmetic coder without multiplications [6].

For example, let us consider a state machine based probability estimation in state-of-the-art M-coder [7] from H.264/AVC and HEVC standards. In the M-coder input symbols are divided into two types: Most Probable Symbols (MPS) and Least Probable Symbols (LPS). State machine contains 64 states. Each state s defines probability estimation for Least Probable Symbol. Set of probability values $\{\hat{p}_0, \hat{p}_1, ..., \hat{p}_{63}\}$ is defined as:

$$\begin{cases} \hat{p}_s = (1-\gamma)\hat{p}_{s-1}, \text{ where } s = 1, ..., 63, \hat{p}_0 = 0.5, \\ \gamma = 1 - \left(\dfrac{\hat{p}_{min}}{0.5}\right)^{\frac{1}{63}}, \hat{p}_{min} = 0.01875. \end{cases} \tag{12}$$

Probability estimation for symbol x_{t+1} is calculated as

$$\hat{p}_{t+1} = \begin{cases} (1-\gamma)\hat{p}_t + \gamma, \text{ if } x_t = \text{LPS}, \\ \max\{(1-\gamma)\hat{p}_t, \hat{p}_{min}\}, \text{ if } x_t = \text{MPS}, \end{cases} \tag{13}$$

and implemented by using tables *TransStateLPS*$[s]$ and *TransStateMPS*$[s]$ which contain number of the next probabilities after compression of the current symbol. It is important to notice that if we define $\gamma = 1/W$, then it is easy to see that the probability estimation rule (13) is based on rule (11).

To remove the multiplication in line 1 of Algorithm 1, M-coder uses its approximation [30]. After the renormalization procedure in Algorithm 2, register R satisfies the following inequality:

$$\frac{1}{2} 2^{b-1} \leq R < 2^{b-1}. \tag{14}$$

From (14) it follows that a multiplication can be approximated in the following way:

$$T = R \times \hat{p}_t \approx \alpha 2^{b-1} \times \hat{p}_t, \tag{15}$$

where $\alpha \in [\frac{1}{2}, ..., 1)$. To improve the precision of the approximation, the M-coder quantizes the interval $[\frac{1}{2}2^{b-1}; 2^{b-1})$ uniformly to four cells. Then each multiplication of the corresponding probability $\hat{p}_s$ and the interval cell with index $\Delta \in \{0, 1, 2, 3\}$ are stored in two-dimensional table *TabRangeLPS*$[s][\Delta]$ which contains 64×4 values.

Thus, the adaptive binary arithmetic coding algorithm in H.264/AVC and HEVC standards is implemented in the following way (see Algorithm 3).

B. Look-up table-free implementation based on virtual sliding window

Based on (10), a probability estimation using virtual sliding window was proposed in [10]. Let us multiply both sides

Algorithm 3 : Binary symbol x_t encoding procedure

```
1: $\Delta \leftarrow (R - 2^{b-2}) \gg (b-4)$
2: $T \leftarrow \mathit{TabRangeLPS}[s][\Delta]$
3: $R \leftarrow R - T$
4: if $x_i \neq$ MPS then
5:     $L \leftarrow L+R$
6:     $R \leftarrow T$
7:     if $s = 0$ then
8:         MPS $\leftarrow$!MPS;
9:     end if
10:    $s \leftarrow \mathit{TransStateLPS}[s]$
11: else
12:    $s \leftarrow \mathit{TransStateMPS}[s]$
13: end if
14: call Renormalization procedure
```

of (10) by W:

$$s'_{t+1} = \left(1 - \frac{1}{W}\right) \cdot s'_t + W x_t, \tag{16}$$

where $s'_t = W s_t$. Let us define $W = 2^w$, where w is an integer positive value. After integer rounding of equation (16), we obtain

$$s'_{t+1} = \begin{cases} s'_t + \left\lfloor \dfrac{2^{2w} - s'_t + 2^{w-1}}{2^w} \right\rfloor, \text{ if } x_t = 1 \\ s'_t - \left\lfloor \dfrac{s'_t + 2^{w-1}}{2^w} \right\rfloor, \text{ if } x_t = 0, \end{cases} \tag{17}$$

and the probability of ones is calculated as

$$\hat{p}_t = \frac{s'_t}{2^{2w}}. \tag{18}$$

Thus, the adaptive binary arithmetic coding algorithm based on virtual sliding window is presented in Algorithm 4.

Algorithm 4 : Binary symbol x_t encoding procedure

```
1: $T \leftarrow (R \times s) \gg (2w)$
2: $T \leftarrow \max(1, T)$
3: $R \leftarrow R - T$
4: if $x_t$ =1 then
5:     $L \leftarrow L+R$
6:     $R \leftarrow T$
7:     $s \leftarrow s + ((2^{2w} - s + 2^{w-1}) \gg w)$
8: else
9:     $s \leftarrow s - ((s + 2^{w-1}) \gg w)$
10: end if
11: call Renormalization procedure
```

In comparison with the M-coder, Algorithm 4 provides a better compression efficiency due to an assignment of a specific virtual sliding window length selected according to the statistical properties of the corresponding binary source [10] and using multiplication in interval division part of the arithmetic coder instead of its approximation. Nevertheless, using this multiplications is not efficient, especially for a hardware implementation.

V. The proposed adaptive binary arithmetic coder

To eliminate the multiplication operation from Algorithm 4, we use a similar reasoning as the one described in Section IV. Let us multiply both sides of (10) by $\alpha 2^{b-1}$:

$$s'_{t+1} = \left(1 - \frac{1}{W}\right) \cdot s'_t + \alpha 2^{b-1} x_t, \tag{19}$$

where $s'_t = \alpha 2^{b-1} s_t$. After integer rounding of equation (19), we obtain

$$s'_{t+1} = \begin{cases} s'_t + \left\lfloor \dfrac{\alpha 2^{b-1} 2^w - s'_t + 2^{w-1}}{2^w} \right\rfloor, \text{ if } x_t = 1 \\ s'_t - \left\lfloor \dfrac{s'_t + 2^{w-1}}{2^w} \right\rfloor, \text{ if } x_t = 0, \end{cases} \tag{20}$$

Taking into account (14) and (15)

$$T = R \times \hat{p}_t \approx \alpha 2^{b-1} \times \hat{p}_t = \frac{s'_t}{2^w}. \tag{21}$$

To improve precision of the approximation (as in M-coder) we quantize the interval $[\frac{1}{2} 2^{b-1}; 2^{b-1})$ to four points:

$$\left\{ \frac{9}{16} 2^{b-1}, \frac{11}{16} 2^{b-1}, \frac{13}{16} 2^{b-1}, \frac{15}{16} 2^{b-1} \right\}. \tag{22}$$

To implement this, we first calculate a state s'_t using (20) for $\alpha = \frac{9}{16}$. Then we approximate the multiplication in the following way:

$$T = R \times \hat{p}_t \approx \frac{s'_t + \Delta \times \frac{1}{4} s'_t}{2^w}, \text{ where } \Delta = \frac{R - 2^{b-2}}{2^{b-4}}. \tag{23}$$

Taking into account that the approximation of the multiplication is correct for $\hat{p}_t < \frac{2}{3}$ [30], we should work with $\hat{p}_t \in [0, .., 0.5]$ and use the Most Probable Symbol and the Least Probable Symbol. In our case, the MPS value should be changed if

$$\hat{p}_t = \frac{s'_t}{2^w} \frac{1}{\alpha 2^{b-1}} > 0.5, \tag{24}$$

or

$$s'_t > \alpha 2^{b-2} 2^w. \tag{25}$$

Thus, taking into account (20), (23) and (25), an adaptive binary arithmetic coding is proposed in the following way (see Algorithm 5):

Since $\Delta \in \{0, 1, 2, 3\}$, a multiplication in line 2 of Algorithm 5 can be implemented based on conditional and addition operations.

From Algorithm 5, it follows that if initial state $s_0 \geq 2^{w-1} - 1$, then the minimum value of the probability estimation is

$$\hat{p}_{min} = \frac{2^{w-1} - 1}{\alpha \cdot 2^{b-1} \cdot 2^w}. \tag{26}$$

Algorithm 5 : Binary symbol x_i encoding procedure

```
1: $\Delta \leftarrow (R - 2^{b-2}) \gg (b-4)$
2: $T \leftarrow (s + \Delta \times (s \gg 2)) \gg w$
3: $T \leftarrow \max(1, T)$
4: $R \leftarrow R - T$
5: if $x_i \neq$ MPS then
6:     $L \leftarrow L+R$
7:     $R \leftarrow T$
8:     $s \leftarrow s + ((\alpha 2^{b-1} 2^w - s + 2^{w-1}) \gg w)$
9:     if $s > \alpha 2^{b-2} 2^w$ then
10:        MPS ←!MPS;
11:        $s \leftarrow \alpha 2^{b-2} 2^w$;
12:    end if
13: else
14:    $s \leftarrow s - ((s + 2^{w-1}) \gg w)$
15: end if
16: call Renormalization procedure
```

VI. Performance evaluation of the proposed coder

A. Coding redundancy analysis

Let us assume that a stationary binary memoryless source with probability of ones p is to be compressed. Then the probability estimation process can be represented by the Markov chain with a finite number of states. Therefore, a coding redundancy $r(p)$ caused by the probability estimation precision can be calculated as:

$$r(p) = \sum_i \pi(s_i) \cdot \Big(-(1-p) \cdot \log_2 (1-\hat{p}_i) - p \cdot \log_2 \hat{p}_i \Big) - h(p), \tag{27}$$

where $\pi(s_i)$ is a stationary probability of state s_i, $\hat{p}_i$ is a probability estimation value for this state, and $h(p)$ is the entropy of the source.

In practice, a coding redundancy also depends on the number of bits b for representation of registers L and R [31]. Taking this into account, we estimate the coding redundancy as

$$r(p) = \lim_{N \to \infty} \left(\frac{R}{N} \right) - h(p), \tag{28}$$

where N is the number of input binary symbols and R is the size of the compressed bit stream.

Table I show the coding redundancy (28) related to the binary entropy for the M-coder and the proposed coder with window lengths $W = 2^4$, 2^5 and 2^6, respectively. For both coders we set the values $b = 10$ and $N = 10^8$.

First, one can see that the coding redundancy for the proposed algorithm depends on the window length W: longer window length provides less redundancy. Second, in most of the cases, in comparison with the M-coder the proposed coder exhibits a higher redundancy if $W = 2^4$ and a lower redundancy if $W = 2^6$. For $W = 2^5$ it has a higher redundancy for low probabilities and a lower redundancy for high probabilities of ones. Finnaly, Table II shows the minimum probability estimation value $\hat{p}_{min}$ for both coders. One can see that the proposed coder provides significantly less $\hat{p}_{min}$ value and; therefore, it is more efficient for compressing low entropy sources.

TABLE I
Coding redundancy $r(p)$ for the M-coder and the proposed coder

p	M-coder	Proposed coder $W = 4$	Proposed coder $W = 5$	Proposed coder $W = 6$
0	0.029	0.0039	0.0039	0.0039
10^{-5}	0.0287	0.0037	0.0037	0.0037
10^{-4}	0.0281	0.0034	0.0033	0.0033
10^{-3}	0.0239	0.0021	0.0019	0.0016
10^{-2}	0.0102	0.011	0.0078	0.0052
0.02	0.008	0.023	0.015	0.008
0.03	0.009	0.03	0.016	0.007
0.04	0.012	0.034	0.017	0.008
0.06	0.017	0.034	0.015	0.006
0.08	0.02	0.033	0.014	0.007
0.1	0.021	0.031	0.014	0.006
0.2	0.021	0.027	0.013	0.007
0.3	0.022	0.028	0.014	0.007
0.4	0.02	0.024	0.013	0.008
0.5	0.02	0.02	0.01	0

TABLE II
Minimum probability estimation value for the M-coder and the proposed coder

coder	$\hat{p}_{min}$
M-coder	0.01875
Proposed coder, $W = 2^4$	0.00152
Proposed coder, $W = 2^5$	0.00163
Proposed coder, $W = 2^6$	0.00168

B. Speed of probability adaptation analysis

In the case of non-stationary source compression, the coding efficiency is highly depend on the speed of the probability adaptation. For quantitative comparison for different probability estimation algorithms, we propose the following approach. First, the initial value of the probability estimation is set to $\hat{p}_0 = 0.5$. Then, the binary source with probability of ones $p < 0.5$ is generated and compressed. Finally, the speed of the probability adaptation is defined as the inverse of the average number of binary symbols t which are needed for the first attainment of probability estimation value $\hat{p}_t \leq p$.

Table III shows the average number of binary symbols for the M-coder and the proposed coder with window lengths $W = 2^4$, 2^5 and 2^6. First, one can see that the adaptation speed for the proposed algorithm depends on the window length W: a shorter window length provides a higher adaptation speeds. Second, the adaptation speed of the M-coder is less than the one for the proposed coder with $W = 2^4$ and higher for $W = 2^5$ and $W = 2^6$.

C. Computation complexity analysis

From Algorithms 1, 3, 4 and 5 it follows, that the number of operations in the interval division part of an arithmetic coder is directly proportional to the number of input binary symbols.

TABLE III
THE AVERAGE NUMBER OF BINARY SYMBOLS t WHICH IS NEEDED TO TRANSFER FROM $\hat{p}_0 = 0.5$ TO $\hat{p}_t \leq p$

p	M-coder	Proposed coder $W = 4$	Proposed coder $W = 5$	Proposed coder $W = 6$
0.45	19	11	31	71
0.4	25	18	45	104
0.3	34	28	63	145
0.2	44	35	80	181
0.1	54	44	99	219
0.05	66	52	115	249
0.02	76	62	133	283

On the other hand, the number of times steps in lines 2–12 are used is proportional to the number of bits in the output bit stream (see Algorithm 2). Let us define N as a number of the input binary symbols, R as a size of the output bit stream. Then, the complexity per input symbol for the binary arithmetic coder C can be written as follows [19]:

$$C = \frac{\alpha \cdot N + \beta \cdot R}{N}, \qquad (29)$$

where α is the computation complexity of the interval division part per input binary symbol, β is the computation complexity of the renormalization part per output binary symbol. For arithmetic coder the output bit stream size

$$R = N \cdot \big(h(p) + r(p)\big), \qquad (30)$$

where $h(p)$ is an entropy of binary memoryless source with probability of ones p, $r(p)$ is an coding redundancy. Therefore, the complexity per input symbol is a linear function of the source entropy and coding redundancy:

$$C(p) = \alpha + \beta \cdot (h(p) + r(p)) \,. \qquad (31)$$

From (31) it follows, that for zero-entropy source ($h(p) = 0$) the complexity $C(p)$ is the lowest possible and is mainly determined by the complexity of the division part. With an increase of $h(p)$ the renormalization part is used more and more often; therefore, the complexity also increases and reaches the maximum value when $h(p) = 1$. Moreover, from the model (31) it follows, that if everything else being equal, the compression scheme which has a higher coding redundancy has a higher complexity.

Table IV shows the complexity $C(p)$ for the M-coder and the proposed coder. In this work, as in many papers related to complexity comparisons (see, for example [32], [33]), we measure the complexity in CPU cycles. For the measurements both coders were implemented as separate software programs which include the encoding of a binary string only. For each probability p we have generated $N = 10^8$ input binary symbols and, then, the CPU cycles of Processor Intel Core i3M 2.1 GHz was measured by the *Average CPU Cycles* software[2]

First, one can observe that the complexity for the proposed algorithm depends on the window length W, which determines different coding redundancies: a longer window length provides less redundancy and, as it is shown in the model (31), less complexity. Second, the proposed coder has up to 18% less computation complexity for very low entropy sources, because its minimum possible probability estimation $\hat{p}_{min}$ is more than 10 times smaller than in the M-coder (see Table II). Therefore it has less redundancy $r(p)$ and, following model (31), the renormalization step is not so often used as in the case of the M-coder, which explains the lower complexity. Finally, for the remaining probabilities, the complexity difference is in the range of $\pm 5\%$, which means that in these cases the complexities of both coders are comparable.

[2]http://user.tninet.se/~jad615g/averagecpu/

TABLE IV
CPU CYCLES PER SYMBOL OF PROCESSOR INTEL CORE I3M 2.1 GHZ FOR M-CODER AND THE PROPOSED CODER

p	0	0.05	0.1	0.2	0.3	0.4	0.5
Proposed coder, $W = 4$	15.5	28.3	35.4	45.1	51.7	56.5	56.6
Proposed coder, $W = 5$	15.5	27.6	34.7	44.5	50.2	55.2	55.3
Proposed coder, $W = 6$	15.5	27.4	34.3	43.4	49.1	54.3	54.0
Proposed coder, average	15.5	27.8	34.8	44.3	50.3	55.3	55.3
M-coder	19.0	28.1	35.5	45.9	52.3	55.3	53.7
Average gain, %	***18.8***	***1.1***	***2.1***	***3.5***	***3.8***	***0.0***	***-3.0***

VII. Application of the proposed coder in H.264/AVC and HEVC standards

A. Scenario 1: Using fixed window length for all contexts

For practical experiments the proposed adaptive binary arithmetic coder was embedded into the JM codec v.12.1 [34] which is the reference software of the H.264/AVC video coding standard and into the HM 3.0 reference software [8] of the HEVC video coding standard. JM codec was used the Main profile, while HM codec was running with the low-delay configuration.

The initial state for each binary context was calculated as:

$$s_0 = \max\left\{2^{w-1} - 1,\, \left\lfloor \alpha 2^{b-1} 2^{w} \hat{p}_0 + 0.5 \right\rfloor \right\} \qquad (32)$$

where $\hat{p}_0$ is the initial probability predefined in the standards.

In fact, the predefined initial probability can differ significantly from the best initial probability for the current binary source from the compression efficiency point of view. Therefore, it is important to use a high speed of probability adaptation at the initial stage of the coding, especially in the case of compression of short binary sequences. Then it is better to switch to a probability estimation with a lower adaptation speed, but with a better precision of the probability estimation. This approach is adopted in JPEG2000 [2] utilizing three adaptation mechanisms, which are embedded into one state machine. It has also been used in [10] by applying Krichevsky-Trofimov formula at the initial stage of the coding. However, in both cases, an additional table or a division operation is needed.

In this paper we implement a similar idea in the following way. First, for a binary sequence compression a small window length $W = 2^w$ is used. After the compression of n_1 binary symbols the window length and the state s are increasing two times to $W = 2^{w+1}$ and $2s$. Then, after the compression of n_2 binary symbols the window length and the state are increased two times again, and so on, until the maximum window length is achieved. In this case, as it is shown in Section VI, a high speed of probability adaptation is achieved by setting small window lengths at the initial stage of coding and, then, a high probability estimation precision is achieved by setting longer window lengths.

Bitrate savings in percentage related to the M-coder for different quantization parameters are presented in Tables V–VI. In all cases the reconstructed video for the corresponding quantization parameter (QP) is identical for the M-coder and for the proposed coder. Practical results were obtained for the first 60 frames of the test video sequences [35], [36] with different frame resolutions: 352×288 ("Foreman", "Mobile", "Akyio", "Mother Daughter"), 640×480 ("Vassar", "Ballroom"), 704×576 ("City", "Crew") and 1920×1080 ("Pedestrian Area", "Rush Hour", "Station", "Tractor"). In our experiments, in case of H.264/AVC, for all contexts an initial window length is $W = 2^4$, the maximum window length is $W = 2^6$ and the values $n_1 = 24$ and $n_2 = 48$. In case of HEVC, an initial window length is $W = 2^3$, the maximum window length is $W = 2^6$ and the values $n_1 = 12$, $n_2 = 24$ and $n_3 = 48$.

The results show that for fixed visual quality the proposed adaptive binary arithmetic coder allows to decrease the bitrate by 0.5–2.3% for H.264/AVC standard and 0.6–3.6% for HEVC standard on average. Herewith, for low QP's (0–30) the bitrate savings is caused mostly by less coding redundancy of window length $W = 2^6$, while for high QP's (40–50) the savings results mostly from the higher speed of the probability adaptation, which is very crucial for encoding of short binary sequences. It is important to notice, that for an implementation of the proposed approach additional tables or multiplication/division operations are not needed. Therefore, in this scenario the computation complexity is comparable with the M-coder.

TABLE V
BITRATE SAVINGS (IN %) COMPARED TO THE M-CODER FOR H.264/AVC STANDARD IN CASE OF USING FIXED WINDOW LENGTH

QP	0	10	20	30	40	50
Foreman	0.93	0.46	0.43	0.10	0.02	0.15
Mobile	0.04	0.17	0.30	0.46	0.20	0.49
Akyio	0.85	0.43	0.12	-0.17	0.68	5.04
Mother Daughter	1.14	0.81	0.56	0.06	0.44	4.81
Vassar	1.35	0.77	0.81	0.42	1.72	8.25
Ballroom	1.23	0.66	0.62	0.50	0.51	0.84
City	0.79	0.53	0.58	0.73	0.60	1.24
Crew	1.01	0.43	0.73	0.59	0.79	1.58
Pedestrian Area	1.14	0.69	0.72	0.79	1.07	1.47
Rush Hour	1.19	0.87	0.88	0.98	0.97	1.46
Station	1.39	1.06	1.07	0.59	0.70	1.20
Tractor	1.02	0.53	0.61	0.79	0.84	0.96
Average	**1.01**	**0.62**	**0.62**	**0.49**	**0.71**	**2.29**

B. Scenario 2: Adaptive window length selection for each context

As it was mentioned in the introduction, from a compression efficiency point of view, it is better to find the trade-off between the adaptation speed and the precision of the probability estimation for each binary source. In the proposed adaptive

TABLE VI
BITRATE SAVINGS (IN %) COMPARED TO THE M-CODER FOR HEVC STANDARD IN CASE OF USING FIXED WINDOW LENGTH

QP	0	10	20	30	40	50
Foreman	0.64	0.58	0.32	0.18	0.80	2.76
Mobile	0.45	0.35	0.52	0.72	1.23	2.80
Akyio	0.75	0.73	0.63	0.74	2.07	6.18
Mother Daughter	0.74	1.06	0.89	0.89	2.21	5.54
Vassar	0.49	0.29	0.96	0.73	1.57	6.27
Ballroom	0.40	0.27	0.44	0.46	1.01	1.93
City	0.52	0.56	0.91	1.04	1.94	3.37
Crew	0.58	0.59	0.78	0.52	1.18	3.98
Pedestrian Area	0.72	0.75	0.61	0.66	0.87	1.54
Rush Hour	0.79	0.91	0.75	0.82	0.91	1.66
Station	0.78	1.01	0.87	0.62	0.95	2.72
Tractor	0.48	0.52	0.62	1.38	2.73	4.31
Average	**0.61**	**0.63**	**0.69**	**0.73**	**1.46**	**3.59**

binary arithmetic coder, this trade-off can be realized due to an assignment of a specific window length selected according to the statistical properties of the corresponding binary source.

In this paper we proposed to select the window length adaptively during the encoding and decoding process. Let us demonstrate this approach for the H.264/AVC standard. First $n_1 + n_2$ binary symbols are coded and decoded by the basic scheme described in Section VII-A. Then after the processing each binary symbol, the encoder and the decoder synchronously estimate the bit stream size $\hat{r}(w)$ for each window length from the set $W = 2^w \in \{2^4, 2^5, 2^6, 2^7\}$. To accomplish this, Algorithm 5 with the virtual renormalization procedure (see Algorithm 6) is applied for each window length. Then after processing of n_3 symbols the encoder and the decoder uses the window length

$$w^* = \arg\min_{i \in \{w\}} \hat{r}(i) \tag{33}$$

until the end of the binary sequence.

Algorithm 6 : Virtual renormalization procedure

```
1:  while $R(w) < 2^{b-2}$ do
2:      if $L(w) \geq 2^{b-1}$ then
3:          $\hat{r}(w) \leftarrow \hat{r}(w) + 1$
4:          $L(w) \leftarrow L - 2^{b-1}$
5:      else if $L(w) < 2^{b-2}$ then
6:          $\hat{r}(w) \leftarrow \hat{r}(w) + 1$
7:      else
8:          $\hat{r}(w) \leftarrow \hat{r}(w) + 1$
9:          $L(w) \leftarrow L(w) - 2^{b-2}$
10:     end if
11:     $L(w) \leftarrow L(w) \ll 1$
12:     $R(w) \leftarrow R(w) \ll 1$
13: end while
```

Bitrate savings related to the M-coder in the case of adaptive window length selection with $n_3 = 512$ are presented in Table VII. One can see that using different window lengths decreases up to 0.3% the bitrate additionally in comparison to the first scenario. On the other hand, because use of virtual renormalization, the complexity of this approach is much higher than the one in Scenario 1.

TABLE VII
BITRATE SAVINGS (IN %) COMPARED TO THE M-CODER IN CASE OF ADAPTIVE WINDOW LENGTH SELECTION FOR EACH CONTEXT

QP	0	10	20	30	40	50
Foreman	1.01	0.56	0.44	0.10	0.02	0.15
Mobile	0.05	0.25	0.37	0.50	0.21	0.48
Akyio	0.89	0.45	0.12	-0.17	0.68	5.04
Mother Daughter	1.26	0.92	0.59	0.06	0.39	4.81
Vassar	1.56	0.94	1.00	0.43	1.63	8.33
Ballroom	1.42	0.83	0.71	0.51	0.52	0.83
City	0.88	0.63	0.73	0.82	0.72	1.32
Crew	1.14	0.60	0.85	0.63	0.82	1.61
Pedestrian Area	1.34	0.90	0.88	0.91	1.22	1.68
Rush Hour	1.41	1.09	1.06	1.13	1.11	1.75
Station	1.69	1.30	1.35	0.70	0.87	1.42
Tractor	1.18	0.70	0.76	0.91	0.93	1.11
Average	**1.15**	**0.76**	**0.74**	**0.55**	**0.76**	**2.38**

VIII. CONCLUSION

A new efficient multiplication-free and look-up table-free adaptive binary arithmetic coder was presented. In comparison to the M-coder it has the following advantages:

1) It does not use any look-up tables allowing a reduction in memory consumption or chip area in a hardware implementation.
2) It provides a simply mechanism to control the trade-off between the speed of probability adaption and the precision of probability estimation through a single parameter, the window length.
3) It provides bitrate savings from 0.5 to 2.3% for H.264/AVC standard and from 0.6 to 3.6% for HEVC standard on average and has a comparable computational complexity.
4) It does not require any changes in the context-modeling and can be easily embedded for performance improvement to any compression scheme which is based on binary arithmetic coding.

Taking into account these advantages, the proposed coder can be more preferable for a future image and video coding standards or non standardized codecs.

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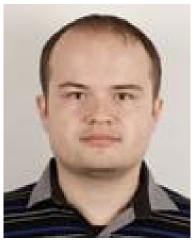

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