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Video Coding for Machines with Neural-Network-based Chroma Synthesis

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ABSTRACT Video coding for machines is an emerging area within video compression technology that has recently attracted considerable research attention. Within the ISO/IEC standardization activities, efforts are underway to develop a new standard optimized for machine vision tasks, rather than just for human-oriented video consumption. In this context, the novel contribution of this work is the application of neural networks to perform chroma synthesis at the decoder side, thus eliminating the need for direct chroma transmission. This concept has been implemented and validated in the Video Coding for Machines Reference Software (VCM-RS), a test model developed by the MPEG Video group, which is briefly described for completeness. Experimental results reported in this paper show that our approach significantly reduces the number of bits required for video representation, achieving bitrate savings of up to 60% for certain video sequences. The presented proposal has been accepted in the current version of the specification of the upcoming VCM standard.

INDEX TERMS chroma representation, chroma synthesis, colorization, video coding for machines

I. INTRODUCTION

According to the reports from data transmission monitoring companies, the vast majority (more than 80%) of information transmitted today is video data [1-2]. Over the last four decades, several generations of human-optimized video coding techniques have been developed in an attempt to cope with the aforementioned increased amount of transmitted video. Among such video coding technologies, the most recent one is VVC [3-4].

In recent years, the volume of video surveillance material has exceeded the level manageable by human observers. In addition, the proliferation of the Internet of Things, semi- and fully autonomous vehicles, AI-based video analytics, the use of intelligent video surveillance, and video-based control in many new fields are just some of the factors contributing to the rapid increase in the amount of video data shared between computers, where direct human consumption of the decoded video is not the primary application [5]. These factors have sparked research interests in video coding, where the decoded data serves as input for machine vision tasks, leading to the proposal of several techniques [6-13].

During the second decade of the 21st century, the abovementioned problems have been recognized, and the term *'video coding for machines* (VCM)' has come into use [6-13].

The need for a standardized video coding framework for machine-centric applications has been recognized by the ISO/IEC Moving Picture Experts Group (MPEG). In 2019, the MPEG Video Coding for Machines (VCM) Ad-Hoc group began works towards a future standard to enable efficient compression for machine vision and hybrid machine-human-vision tasks. By 2021, VCM had outlined initial requirements for applications such as surveillance, intelligent transportation, and smart cities, reflecting the growing role of machine-driven algorithms for visual data processing [5]. Due to the complexity of these domains, the standardization process was split into two tracks: one focused on enhancing traditional video compression methods and the other on compressing visual features (Feature Coding for Machines [14]). For the first track mentioned, in 2022, a revised Call for Proposals (CfP) [15] solicited contributions from global research institutions, leading to the formation of the Video Coding for

Machines (VCM) standardization project, which continues to drive advancements in the field.

II. MPEG VCM CODEC

The MPEG VCM approach is codec-agnostic, separating VCM-specific tools from the core video codec (the "Inner Codec"), such as HEVC or VVC (see Fig. 1). Although special codec designs have also been studied for this purpose [16-17].

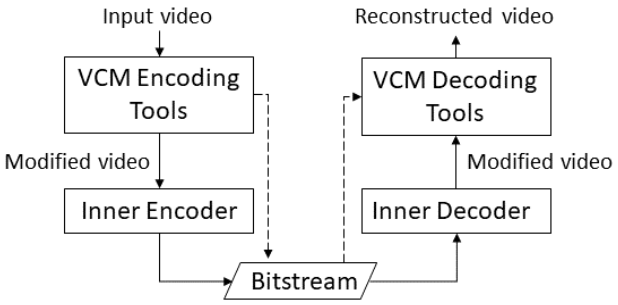

FIGURE 1. The general model of MPEG VCM codec. Dashed lines represent additional data generated by VCM encoding tools and necessary for VCM decoding tools.

The VCM-specific encoding tools transform the video before video is compressed using a standard compression technology. Some of these tools generate additional data that must be transmitted in the compressed bitstream. The VCM-specific encoding tools include spatial and temporal resampling, region-of-interest (RoI) encoding [18-20], and bit-depth truncation. Temporal downsampling reduces the frame rate by discarding and interpolating frames during encoding and decoding. Spatial downsampling reduces the resolution of video frames in a way that balances bitrate reduction with preserving the detail necessary for machine vision, while also reducing computational complexity. RoI encoding prioritizes key regions within a frame for high-quality encoding, while less important areas are grayed or discarded. A RoI usually corresponds to the area of an object and its nearest neighborhood. Bit-depth truncation reduces the luma component's dynamic range (e.g., from 10 to 9 bits) in order to reduce the bitrate without significantly affecting video quality.

After encoding using VCM tools, the resulting video is encoded by an Inner Encoder, typically VVC [3-4], or its extensions in current MPEG experiments. The compression efficiency is evaluated using selected machine vision tasks performed by artificial neural networks. The machine vision tasks usually tested are object detection and object tracking.

The novelty of this paper consists in application of an additional new tool extending the set of VCM-related encoding and decoding tools. The new encoding tool is Chroma Removal and Control, whereas the new decoding tool is Chroma Restoration. The idea is to remove chroma data at the input of the Inner Encoder and restore chroma at the output of Inner Decoder, Chroma Restoration exploits some additional data produced by Chroma Removal and Control that are transmitted in the bitstream (see Fig. 2). The bitrate for this additional data is relatively low, therefore the amount of data is reduced at the input to the Inner Encoder is lower, thus increasing compression performance of the system,

III. VIDEO COLORIZATION – EXISTING APPROACHES

Color information plays a crucial role as contextual input in tasks such as object detection, segmentation, and classification, particularly in scenarios requiring differentiation between objects with similar geometric structures.

In the VCM framework, chroma is subject to lossy compression and quantization with the goal of balancing bitrate cost against quality loss. Consequently, although chroma still accounts for a noticeable portion of the overall bitrate, its degradation also leads to a noticeable degradation in the performance of machine vision tasks. This study aims to evaluate whether a more efficient representation can be achieved by completely omitting chroma during transmission and reconstructing it at the decoder side from luminance alone using colorization.

The colorization of a video sequence is a popular topic in computer vision [21]. The development of Artificial Neural Networks (ANN) resulted in the development of multiple methods for automatic colorization of grayscale images and videos. Depending on the use case, an ANN may colorize, e.g., a part of a grayscale image [22-24], may use additional color distribution hints [23, 25-26] or a sparse grid of color samples [23, 27]. A colorization technique may also be additionally guided by indicating a reference image [28], a color palette [29], or even by text prompts [30-31]. Another approach is embodying the color hints in grayscale image [32]. In the case of a video sequence, the colorization algorithm can use temporal hints for the continuity of reproduced colors [33]. The colorization algorithm may colorize the whole image at once, or colorize subsections of the image, according to performed semantic segmentation [34-37].

Convolutional neural networks are used in most methods for the abovementioned use cases. One of the popular approaches is the use of the U-net architecture [23, 25, 38-39] as the main colorization ANN, which is trained as a part of a Generative Adversarial Network (GAN) network [23, 25, 39-41]. In most cases, the ANN estimates all image color components at once. However, in some methods, the color components are estimated separately [37, 41].

With the advancements in colorization methods, their usage for image and video compression was considered [42-44]. Peter [45] proposed to dedicate more bits for luma than for chroma during the encoding, and then restore the color on the decoder site. Some researchers [46-47] proposed to transmit the luma component only, and colorize the sequence in the decoder. In Cui [48], a single color component is first reconstructed and then used to restore the other one.

Most of the respective image and video compression methods use colorization as a postprocessing step after decoding the grayscale content. Additionally, the techniques are dedicated to human consumers and typical natural content.

For video coding for machines, it is essential to understand how image colorization affects the performance of machine vision tasks like object detection, segmentation, and classification.

Zhu et al. [49] examined the impact of inaccurate RGB data on segmentation accuracy in colorized point clouds. Two types of inaccuracies have been considered: incorrect color and similar color information, both of which significantly reduced performance. The study employed the DeepLabV3+ model, assessing results using Overall Accuracy (OA) and Mean Intersection over Union (mIoU).

Singh et al. [50] explored applications of Convolutional Neural Networks (CNN) and how color information influences CNN performance in object recognition. They trained models on original color images, grayscale images, and images with altered color distributions to assess reliance on color cues. The results indicate that, while CNNs can recognize objects without color, accurate color cues obviously enhance classification accuracy, highlighting the role of colorization in object classification tasks.

These considerations underscore the importance of accurate color information in improving the performance of detection, segmentation, and classification algorithms.

Unfortunately, the subject of colorization in video coding for machines remains nearly unexplored. In this paper, the idea of colorization is explored and tested in VCM. Here, colorization is considered as one of the coding steps, which is also the novelty of this work.

IV. MAIN IDEA

The main idea of the paper is to synthesize chroma at the decoder side (from the luma component alone) instead of transmitting it directly. The application of this idea within the MPEG VCM framework [51] is illustrated in Fig. 2. When the proposed new compression tool is used, the chroma is cleared prior to further processing in the encoder (before the Spatial Downsampling tool is activated) thus allowing for bitrate savings in the Inner Encoder. The rationale for that is the observation that exact color impression is mostly not crucial for machine vision, but color differences often play a critical role in machine vision.

In the proposed approach, chroma synthesis (restoration) is implemented with the use of an Artificial Neural Network (ANN). At its input, only the decoded luma samples are available. Obviously, chroma synthesis in such a case provides only an approximation of the original chroma, which may be insufficient for some sequences in some applications. Therefore, we also propose a control mechanism that enables or disables the proposed chroma synthesis tool. The decision is made at the encoder in an automated way, based on correlation metric (see Section V B). Through this paper, we call the MPEG VCM codec with the abovementioned modifications the Modified MPEG VCM Codec.

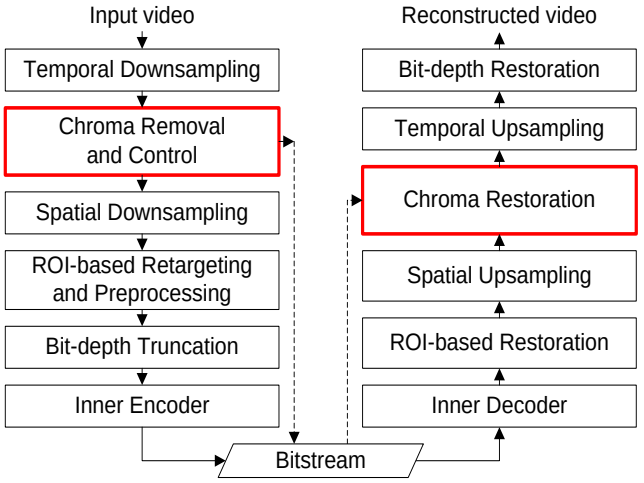

FIGURE 2. The application of the proposed idea within the MPEG VCM framework. The new stages added by this work are marked in red. The dashed lines represent the additional data generated by Chroma Removal and Control that is necessary for Chroma Restoration. For the sake of clarity, the other additional data produced by VCM Coding Tools are omitted.

V. PRACTICAL IMPLEMENTATION OF THE MODIFIED MPEG VCM CODEC

A. NEURAL NETWORK

As a colorization method, we choose the SIGGRAPH17 method [23], available as an open-source package [52]. In the experiments executed by the authors, two other models (ECCV [22] and DeOldify [53]) were tested, but SIGGRAPH17 gave the best results. The SIGGRAPH17 uses one of the popular approaches to colorization with ANN: U-net-like convolutional network [38], which is trained as a part of the GAN network [40]. The network architecture is presented in Fig. 3. Such a network is a good reference for other approaches. The model is adapted for processing and outputting frames of size 256×256 represented in CIE Lab color space [54]. The network is trained using the ImageNet dataset [55].

The input video samples are represented in the YCbCr color system, and the 4:2:0 chroma subsampling scheme is used. Before colorization, fame contains a luma component only. In order to keep compliance with the software used, the luma samples are converted to RGB, and then RGB samples are converted to CIE Lab color coordinates [56]. Only the L component is inputted to the network (ANN). Lastly, the frame is downscaled to the size of 256×256.

The ANN outputs a and b color components. The ANN input (L) is concatenated with the output to get the color frame. Then, the frame is resized to the original resolution, and color conversion from CIE Lab, through RGB to YCbCr is

performed. Finally, chromas are subsampled to meet the 4:2:0 chroma sampling scheme.

Notably, the Y component of the resulting frame is copied from the original frame. Effectively, only chroma Cb and Cr channels are modified.

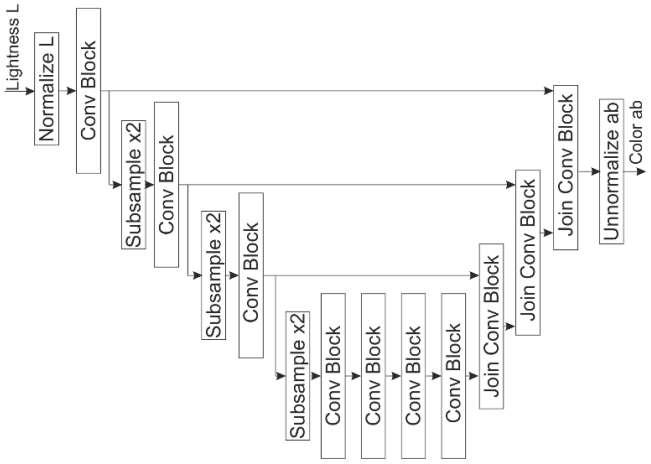

FIGURE 3. The network architecture of the employed ANN model for chroma a and b synthesis for the CIE Lab color space [23].

B. ENCODER OPERATION

The operation of the proposed tool in the MPEG VCM encoder is presented in Fig. 4. As mentioned before, the encoder has to decide whether to enable or disable the proposed colorization based on the potential fidelity of the reconstructed chroma.

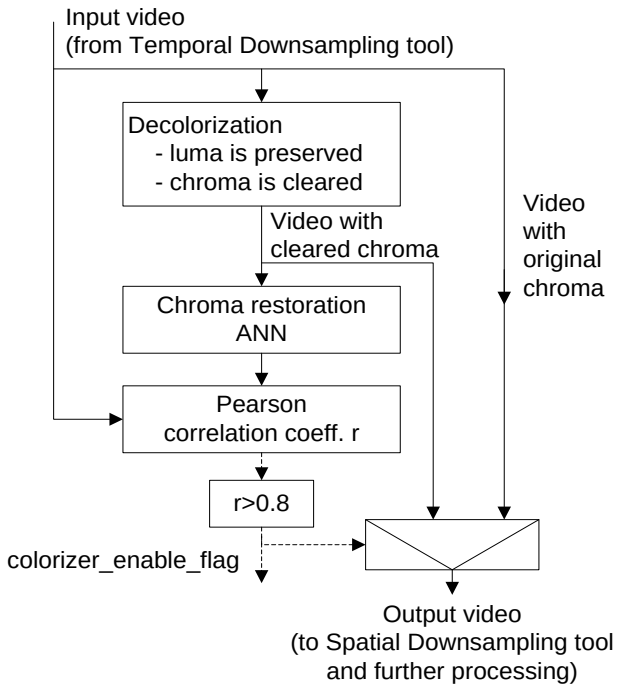

FIGURE 4. Operation of the proposed tool in the encoder.

To estimate that, the chroma is speculatively removed and restored (synthesized). Then, the correlation between the reconstructed chroma and the original chroma is measured using the Pearson Correlation Coefficient (r). High correlation ($r > threshold$) is the condition to turn the proposed tool on (and thus not directly encode the chroma and synthesize it on the decoder side instead). Otherwise, the proposed tool is disabled, and the chroma is encoded as usual. The *threshold* in our method was set to 0.8, based on extensive experiments. In the bitstream, the information about the decision is signaled as a single-bit flag "colorizer_enable_flag" (Fig. 4). This decision is done (and signaled) on the basis of each IDR frame in order to meet random-access requirements in all considered encoding scenarios (see Section VI A).

C. DECODER OPERATION

When the proposed tool is enabled (which is signaled with "colorizer_enable_flag" in the bitstream), it means that the transmitted frame has been decolorized, i.e. contains luma only. In such a case, the chroma components are synthesized using the ANN.

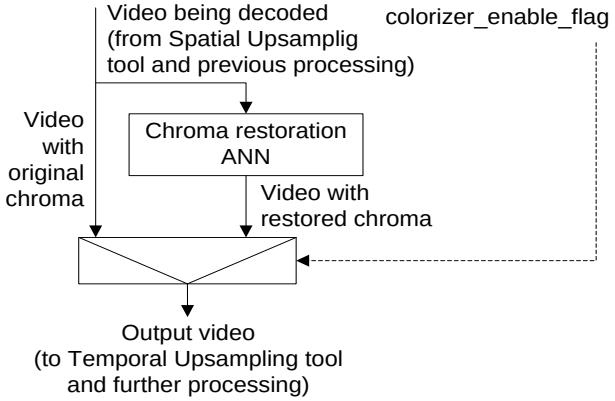

FIGURE 5. Operation of the proposed tool in the decoder.

VI. EXPERIMENTAL VALIDATION

A. CONDITIONS

In order to demonstrate the potential of the presented approach, the method has been implemented in the MPEG VCM reference software [16]. The experiment has been performed according to the MPEG VCM Common Test Conditions (CTC) [51].

The experiment consists of encoding, decoding, and evaluation of SFU-HW and TVD sequences in six scenarios. The comparison is done using the coding results of the current version of the MPEG VCM codec with its default configuration [51].

The MPEG VCM Common Test Conditions (CTC) defines six encoding scenarios, which consist of three configurations: Random Access (RA), Low Delay (LD), and All Intra (AI), in two versions: Inner and End-to-End (E2E) [51]. The difference between Inner and E2E versions of configurations

lays in the scope in which RA/LD/AI temporal requirements are applied. In Inner scenarios, the requirements are applied only on the level of the Inner Codec. In E2E scenarios, the requirements are applied to the whole encoder-decoder system (the Inner Codec and the VCM coding tools, see Fig.1). For LD E2E and AI E2E scenarios, the encoder cannot analyze or use the frames further to this, which is actually encoded. That implies, for example, that the temporal interpolation is to be replaced by extrapolation, which uses only the past frames (in LD E2E), or to be turned off (in AI E2E).

The SFU-HW sequences are divided into four classes according to their resolutions (A: 2560×1600, B: 1920×1080, C: 832×480, D: 416×240).

The mandatory evaluation comprises two machine vision tasks done on the decoded video – Object Detection, done on the SFU-HW dataset, and Object Tracking done on the TVD dataset.

B. EXAMPLES

Example colorized frames compared to the original ones are shown in Fig. 6. As can be seen, the colors are synthesized well, however, in some cases the saturation of colors seems to be lower.

FIGURE 6. Examples of frames: left column - original frame, right column - synthesized chroma [23].

C. RESULTS

The results are presented in Tables I and II as bitrate reduction measured as the Bjøntegaard delta [51] versus the mean average precision (mAP) for object detection and the multiple object tracking accuracy (MOTA) for object tracking. Moreover, the encoding and decoding times are provided for the proposed tool switched on. All the results are provided with respect to the encoder and decoder with the proposed tool switched off. For example, for a given sequence and a given scenario, the value of BD-rate mAP is -14.79%. This means that the average bitrate is reduced by 14.79%, keeping the same mAP for object detection. The relative encoding time of 101% means that switching on the proposed tool increases the VCM encoding time by 1.11%.

From the detailed results (Table II), it can be seen that the method provides interesting results in the cases when the chroma synthesis is turned on. The very small losses in the other cases are caused by the new control bits, which inform the decoder to bypass the colorization tool. Such a loss is negligible as compared to gains achieved by the tool in some other sequences (up to ~60%). Generally, in the context of VCM, the expected error margin due to the noise in metrics like MOTA/mAP is about 1%.

The proposed tool improves the compression efficiency for some sequences. The complexity overhead is mostly below 2.6% for the encoder and below 5% for the decoder.

Table I provides the average results for the sequences tested. The results demonstrate an average bitrate reduction for object tracking of 6.6% to 18.4%, depending on the compression scenario. This percentage reduction is much higher than the percentage increase of the encoding and decoding complexity measured for CPU implementations. Unfortunately, the method does not improve encoding and decoding for object detection. This issue needs some further investigation.

TABLE I
SUMMARIZED RESULTS FOR ALL VCM ENCODING SCENARIOS

Encoding scenario	Object Detection BD-Rate [%] mAP	Object Tracking BD-Rate [%] MOTA	Encoding Time [%]	Decoding Time [%]
Random Access (Inner)	0.04	-14.42	100.64	101.14
Random Access (E2E)	0.03	-12.09	100.57	101.41
Low Delay (Inner)	0.04	-10.79	100.84	101.01
Low Delay (E2E)	0.05	-6.60	100.83	100.95
All Intra (Inner)	0.02	-12.65	100.53	100.64
All Intra (E2E)	0.03	-18.48	100.41	100.82

TABLE II
DETAILED RESULTS FOR RANDOM ACCESS, LOW DELAY AND ALL INTRA ENCODING SCENARIOS

	Random Access (Inner)			Low Delay (Inner)			All Intra (Inner)		
Object Detection	BD-Rate [%] mAP	Encoding Time [%]	Decoding Time [%]	BD-Rate [%] mAP	Encoding Time [%]	Decoding Time [%]	BD-Rate [%] mAP	Encoding Time [%]	Decoding Time [%]
Class A	0.03	100.78	99.75	0.03	100.64	100.18	0.01	100.54	100.08
Class B	0.06	99.85	99.79	0.04	100.49	100.52	0.01	100.53	100.72
Class C	0.03	101.21	100.22	0.02	100.55	99.91	0.03	100.51	100.61
Class D	0.04	100.54	100.26	0.05	101.39	100.55	0.02	101.23	99.85
Average	0.04	100.60	100.01	0.04	100.77	100.29	0.02	100.70	100.32
Object Tracking	BD-Rate [%] MOTA	Encoding Time [%]	Decoding Time [%]	BD-Rate [%] MOTA	Encoding Time [%]	Decoding Time [%]	BD-Rate [%] MOTA	Encoding Time [%]	Decoding Time [%]
TVD-1-1	0.05	100.23	99.74	0.06	100.09	99.83	0.03	100.32	100.64
TVD-1-2	0.09	100.19	100.59	0.12	99.80	99.53	0.03	99.94	100.21
TVD-1-3	0.07	100.12	100.19	0.08	100.16	99.87	0.03	100.11	100.09
TVD-2-1	0.04	99.65	100.02	0.07	100.18	99.81	0.08	100.09	99.51
TVD-3-1	**-14.79**	**101.95**	**105.46**	**1.43**	**101.73**	**104.51**	**-23.29**	**100.53**	**102.22**
TVD-3-2	**-25.43**	**101.25**	**104.38**	**-23.38**	**101.71**	**104.29**	**-25.91**	**100.71**	**101.93**
TVD-3-3	**-60.97**	**101.38**	**105.42**	**-53.90**	**102.60**	**104.21**	**-39.52**	**100.73**	**102.13**
Average	-14.42	100.68	102.26	-10.79	100.90	101.72	-12.65	100.35	100.96
	Random Access (E2E)			Low Delay (E2E)			All Intra (E2E)		
Object Detection	BD-Rate [%] mAP	Encoding Time [%]	Decoding Time [%]	BD-Rate [%] mAP	Encoding Time [%]	Decoding Time [%]	BD-Rate [%] mAP	Encoding Time [%]	Decoding Time [%]
Class A	0.03	100.28	99.95	0.06	100.53	100.03	0.01	100.31	99.99
Class B	0.02	100.05	99.77	0.06	100.42	100.72	0.02	100.56	100.65
Class C	0.03	101.11	101.34	0.03	100.59	100.02	0.02	100.34	100.32
Class D	0.03	100.59	100.85	0.06	101.34	99.87	0.02	100.99	100.23
Average	0.03	100.51	100.48	0.05	100.72	100.16	0.03	100.55	100.30
Object Tracking	BD-Rate [%] MOTA	Encoding Time [%]	Decoding Time [%]	BD-Rate [%] MOTA	Encoding Time [%]	Decoding Time [%]	BD-Rate [%] MOTA	Encoding Time [%]	Decoding Time [%]
TVD-1-1	0.04	100.41	99.84	0.08	100.14	99.76	0.02	100.01	99.92
TVD-1-2	0.10	100.03	100.52	0.15	99.88	99.57	0.03	99.90	99.61
TVD-1-3	0.07	100.02	100.03	0.11	100.21	99.89	0.01	100.05	100.21
TVD-2-1	0.03	99.55	100.93	0.09	100.19	99.83	0.03	100.07	99.93
TVD-3-1	**-12.33**	**102.02**	**105.56**	**-2.04**	**101.76**	**104.64**	**-37.76**	**100.44**	**103.29**
TVD-3-2	**-25.48**	**101.15**	**104.18**	**-13.44**	**101.76**	**104.23**	**-34.17**	**100.64**	**102.55**
TVD-3-3	**-47.07**	**101.23**	**105.33**	**-31.18**	**102.65**	**104.25**	**-57.49**	**100.75**	**103.77**
Average	-12.09	100.63	102.34	-6.60	100.94	101.74	-18.48	100.27	101.33

VII. CONCLUSIONS

This paper introduces a novel neural network-based chroma synthesis tool for video coding for machines (VCM), enabling significant bitrate savings while maintaining high performance in machine vision tasks. Integrated seamlessly into the MPEG VCM framework, the method utilizes an automatic control mechanism at the encoder, which dynamically activates chroma synthesis based on correlation metrics. This approach ensures that the proposed tool is applied adaptively, thus preserving machine vision task performance in diverse video scenarios.

The modified codec was carefully tested under several encoding scenarios defined by MPEG in Common Test Condition document [51]. Experimental results show an average bitrate reduction of 12% in Random Access End-to-End configurations for object tracking tasks, confirming the method's ability to optimize network and storage demands without compromising machine vision accuracy. Importantly, the replacement of the decoded chroma by the synthesized chroma was found to have minimal impact on detection and tracking performance, validating the efficiency of the control mechanisms.

This study lays the groundwork for incorporating advanced chroma synthesis techniques into future VCM standards to address the growing need for efficient machine-oriented video coding. Further research is warranted to explore its applicability to broader machine vision tasks, such as segmentation and classification, and to develop adaptive models for diverse data contexts.

Recently, our method has been thoroughly evaluated by experts working for the ISO/IEC MPEG Video Coding for Machines (VCM) group [57-64]. The refined version of our proposal has been accepted in the current version of the specification of the upcoming VCM standard. This advanced version of the standard is currently formally published as a so-called Committee Draft [65], i.e. the standard proposal submitted to the standardization bodies of the ISO/IEC countries.

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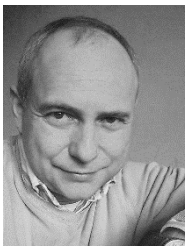

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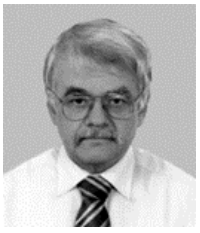

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