Multi-sample Compression of Fingerprints: Can it be done?

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***Abstract*—A recent video-compression based approach extending traditional biometric sample data compression techniques is adapted for fingerprint sample compression for the first time. Besides employment of default H.265 video coding settings (as proposed so far), we thoroughly investigate and optimize codec parameters for the effective compression of biometric sample sets. Compression efficiency and implications on recognition accuracy (as well as biometric quality) are determined using two fingerprint recognition schemes and the four FVC2004 data sets. Results obtained are stable across different recognition schemes and exhibit clearly improved compression behaviour over current ISO/IEC and ANSI/NIST standards for biometric data interchange. For two out of four datasets even better results as compared to BPG compression are observed. This clearly underpins the high potential of multi-sample fingerprint compression given the extremely high sample variability present in the FVC2004 data.**

***Index Terms*—fingerprint sample compression, H.265, JPEG2000, video coding parameters, fingerprint recognition**

I. Introduction

Since biometric data has begun to be stored digitally, minimising file size has been an important concern, in order to increase both storage and transmission efficiency. One way to achieve this is to only store or transmit extracted template data. However, some scenarios require having access to the original image sample data to avoid costly re-enrollment: (i) to be able to recalculate template data in case a different template generation scheme is to be adopted or (ii) after template data have to be revoked and a new generation of cancelable templates is to be generated in a cancellable biometrics approach. In both cases, undesired re-enrollment is avoided once original samples are retained and stored.

Thus, sample data compression has become an almost integral part of biometric systems and typically lossy compression is employed due to the much more significant data reduction achieved (e.g. lossless file or image compression techniques achieve lower compression rates at least by one order of magnitude). Highly effective compression is required once datasets with millions of users and several sample images per user are being stored. However, the distortions introduced by compression artifacts may interfere with subsequent feature extraction and may degrade the biometric comparison scores. Therefore, it is highly profitable to look into the best suited compression methodology for a given biometric modality or even dataset, and to look further into possible interference between compression technology and feature extraction / template generation algorithms. Video compression techniques have been designed to exploit redundancies among frames, thus, these seem to be well suited intuitively to compress biometric datasets exhibiting a high amount of sample correlations.

The certainly most relevant standard for compressing image data used in biometric systems is the ISO/IEC 19794 standard suite on "Biometric Data Interchange Formats" where in the most recently published version (ISO/IEC 19794-4:2011 for fingerprint data), JPEG, JPEG LS, and JPEG2000 are included for lossy compression (see clause 8.3.13), where JPEG2000 is recommended. The ANSI/NIST-ITL 1-2011 standard on "Data Format for the Interchange of Fingerprint, Facial & Other Biometric Information" (former ANSI/NIST-ITL 1-2007) only supports JPEG2000 for applications tolerating lossy compression. In forensic daily work, the FBI WSQ fingerprint compression standard [1], [2] is still being present.

Apart from standardisation, a variety of independent studies dealing with compression and the respective impact on biometric recognition performance exist for various modalities, including fingerprints (e.g. [3], [4], [5]). Also recent learning based compression schemes (including the current JPEG AI candidate methodology) have been applied successfully to fingerprint data [6], [7]. So far, compression impact assessment on fingerprint biometric recognition schemes has been limited to lossy still image coding techniques [8], [6]. In the context of iris [9] as well as finger vein recognition [10], respectively, video coding has been suggested to be applied to groups of samples [9] or entire sample datasets [10] (i.e. multi-sample compression). The impact on recognition performance as compared to the application of still image coding schemes has been demonstrated to be significantly lower. Therefore, in this paper we will investigate if such an approach is sensible as well for fingerprint sample data. This is questionable, as the visual properties of fingerprint samples are fairly different from iris or fingervein samples, respectively. In particular, while iris samples and finger vein samples contain a significant share of uniform or close to uniform areas (e.g. pupil area, sclera area, skin, inter-vessel tissue, background), this is hardly the case for fingerprint samples (apart from image background areas). Thus, exploiting redundancies might turn out to be much more difficult among different samples as done by video

coding systems.

The subsequent section II discusses joint compression of visual biometric sample data and explains the approach pursued in this work. Section III defines the experimental setup including a subsection with thorough discussion of video coding parameters suited to be applied for compressing biometric samples (instead of compressing natural video). Section IV presents experimental results before the paper is terminated with the Conclusion in section V.

II. Biometric (Multi-)Sample Compression

In the last years, several multi-sample fingerprint recognition systems (e.g. [11], [12]) and also fusion approaches [13] have been suggested, some of which use the information of multiple samples captured during enrollment to come up with a consolidated and more robust feature set as compared to using single samples. Note, that also adaptive biometric systems [14] employ several enrollment samples, however, the aim here is slightly different, i.e. to be better able to cope with temporal changes in samples and corresponding templates.

The multi-sample compression scheme proposed here specifically targets the compression of datasets containing several fingerprint sample images of a single finger (which is seen very often in practice), being targeted to multi-sample recognition or adaptive biometric fingerprint systems (where the latter requires a re-compression in case of an updating step).

However, there are significant differences between typical pictorial data as usually compressed by video encoders and collections of (similar) biometric sample image databases. Video compression techniques have been designed to exploit the redundancies present among adjacent (and highly redundant) video frames. This is done by estimating differences among these adjacent frames, which can be caused by camera motion, objects' motion, and illumination or scene changes, respectively. The observed differences are compensated (by exploiting motion information stored in motion vectors on a block-basis) and only the residual error between a macroblock to be compressed and its motion compensated prediction (based on already encoded pictorial data) is actually stored.

In biometric datasets, the differences among samples are of different nature. These are typically caused by (1) subject motion and behavioural / physiological variabilities for samples acquired within a single session, (2) additional environmental changes including illumination variation among samples of different sessions, (3) additional template ageing effects in case sessions are significantly separated in time, and (4) additional inter-subject variability of biometric traits in case samples of different subjects are to be compressed. In any case, considering the high extent of superficial similarity among samples (ridges and valleys), but also the obviously present differences among biometric sample data, it is a somewhat natural idea to employ video coding technology to compress biometric datasets, as both requirements, (i) being able to exploit redundancies among images, as well as (ii) being able to handle occurring differences can eventually be met using existing video compression technology.

An eventually complicating fact is that the application context of the compressed data is very different, i.e., viewing by humans for typical video vs. feature extraction and template comparison for biometric data. Thus, it might turn out, that parameters found to be optimally suited for video compression (of natural video) do not deliver optimal results when used for biometric data. We analyze these effects and provide suggestions how to set parameters for compression of biometric sample data.

Let us assume a biometric data set with N samples per individual trait (i.e. finger in this work) and N_{max} samples overall is compressed into one single video. The GOP size M can be varied between $1 \leq M \leq N_{max}$ (N_{max} may not be admissible due to parameter range restrictions, in this case e.g. an integer multiple of N can be selected as upper range bound, i.e. $M = kN$). It is to be expected that the encoder can exploit the redundancy between different pictures of the same individual trait – thus setting $M = N$ should work decently (the higher N, the more redundancy can be exploited). Setting $M = kN$ as suggested attempts to exploit redundancies among samples from different traits/users. If this is indeed possible, is highly questionable, at least results in [10] show decreasing recognition accuracy results in case of increasing k, for $k > 1$ in the case of finger vein data. While in [10] N_{max} is equal to the overall size of the dataset and only M is varied, [9] sets $N_{max} = N$ and $M \leq N$, thus an independent video is created and compressed per single user. In [10] it is clearly shown that the former strategy is superior in terms of compression effectiveness (mostly due to the significant overhead induced by the video header data for each single individual).

III. Experimental Setup

A. Data

For our investigations, we use the four sets from the fingerprint verification contest 2004 (FVC2004 [15])[1]. Note that although being in use for decades now, these datasets exhibit a particular property which makes them highly challenging for the techniques introduced (and therefore, if results indeed are convincing, other type of fingerprint data may be compressed even more effectively): For these datasets, perturbations have been introduced deliberately – position, rotation, applied pressure, skin distortion and humidity have been varied while sensors have not been cleaned during acquisition. Thus, for exploiting redundancies among samples, as done in video compression, these perturbations of course represent a kind of worst case situation. Databases 1 and 2 contain images of two different optical sensors (DB1, DB2), database 3 originates from a thermal sweeping sensor (DB3), and database 4 consists of (SFinGe) synthetically generated prints (DB4). Each dataset contains 110 fingers with 8 imprints per finger ($N = 8$).

[1] bias.csr.unibo.it/fvc2004/

B. Software

We have applied two different fingerprint recognition schemes, both relying on a comparison of extracted minutiae sets: As a representative for a non-commercial, medium accuracy system, we apply mindtct and bozorth3 from the "NIST Biometric Image Software" (NBIS) package (available at http://fingerprint.nist.gov/NBIS/) for minutiae detection and comparison, respectively. The second technique is a representative from the COTS class, we use VeriFinger, developed by Neurotechnology (VeriFinger SDK 12.0, most recent version available at http://www.neurotechnology.com/verifinger.html), denoted as VF.

The test procedure of the FVC2004 was adopted to determine the EER for fingerprint recognition on compressed data. While we have also computed ZeroFMR as well as FMR1000 values, these exhibit the same trends as seen in the EER data. For the genuine comparisons (mated sample scores, to determine FNMR) each sample of each finger is compared with all remaining samples of the same finger, no symmetric comparisons are performed. For the impostor comparisons (non-mated sample scores, to determine FMR) the first sample of each finger is compared against the corresponding first sample of the same finger of all remaining individuals, again no symmetric comparisons are performed.

As video compression algorithm, instead of considering the most widely used video codec MPEG-4 AVC (H.264), we employ the more recent H.265 / High Efficient Video Coding (HEVC) [16], [17], the ISO/IEC 23008-2:2013 standard. We have also computed results for H.264, but as these exhibit exactly the same trends as H.265 results, we omit these in this paper. For comparisons, we use three different (lossy) image compression techniques:

1) JPEG (jpg): The well-known (ISO/IEC IS 10918-1) DCT-based image compression method [18] based on 8x8 pixels block processing.
2) JPEG 2000 (jp2): The wavelet-based image compression standard (ISO/IEC IS 15444-1) can operate also at higher compression ratios [19] as compared to JPEG. J2K is also a part of the DICOM standard where it replaced lossless JPEG compression. Results typically do not generate block-based artefacts as the original DCT-based JPG standard.
3) Better Portable Graphics (bpg): This algorithm is based on a subset of the H.265 (HEVC, ISO/IEC 23008-2) video compression standard [20] and is optimised for still image coding by minimizing header data related to temporal informations.

To implement JPEG and JPEG2000 compression, we use the `libjpeg` and `libopenjp2` libraries, respectively. For BPG, the Linux distribution obtained from https://bellard.org/bpg/ is used, the software for H.265 /HEVC video compression is x265 from https://bitbucket.org/multicoreware/x265/src.

C. HEVC / H.265 Settings

HEVC / H.265 and its x265 implementation offers a large number of parameters to configure the encoding process. In this subsection, we describe relevant parameters, their default values and their values recommended to be used in the context of bulk biometric sample data compression. We will refer to the x265 parameter documentation[2]. The parameters `--ipratio` and `--pbratio` define how the quantization parameter in P and B frames differs from the quantization parameter in I frames. The default values of 1.4 and 1.3, respectively, yield stronger compression in P frames and yet stronger compression in B frames. When compressing biometric images, these default ratios lead to different quality for different images, depending on whether they happen to be I, P or B frames within a GOP. Even when only small prediction residuals are present, those which critically impact feature-related thresholds put data in P and B frames at a disadvantage compared to residuals in I frames. Thus, as shown in Table I, we set both parameters to 1. Note that there are additional parameters like `--qcomp`, which determines how the quantization parameter is adapted for P and B frames with high residuals. However, it is only relevant when adaptive quantization is enabled. Although this is the case by default, setting an appropriate tuning (see below) disables it and does not make it necessary to set the `--qcomp` and related parameters.

Setting the GOP size or key frame interval requires setting multiple parameters. By default, *x265* attempts to detect scene cuts to place I frames adaptively (parameter `--scenecut`). In regular video material, this detection improves coding efficiency because a frame whose adjacent frames are very dissimilar is not coded based on residuals, i.e., as a P or B frame. However, for biometric images, scene cut detection in general is unlikely to be effective. As discussed previously, a natural approach is to set the GOP size equal to the number of imprints per finger present in the dataset to be compressed. Setting the GOP size itself is done by specifying a minimum (parameter `--min-keyint`) and a maximum value (parameter `--keyint`) – if a fixed GOP size is desired, both parameters need to be set to the same value to avoid fluctuations.

TABLE I: Required *x265* parameters and parameter values for consistent and comparable results when compressing biometric images.

Parameter name	Parameter value	Meaning
`--ipratio`	1	Identical quantization in I and P frames
`--pbratio`	1	Identical quantization in P and B frames
`--scenecut`	0	Disable variable I frame placement
`--min-keyint`	M	Minimum GOP size of M frames
`--keyint`	M	Maximum GOP size of M frames
`--no-deblock`	–	Disable deblocking filter
`--no-sao`	–	Disable SAO filter
`--qp`	Q	Constant quantization parameter (no CRF)
`--no-info`	–	Disable SEI on every key frame
`--tune`	`psnr`	Disable adaptive quantization

Block-based video compression produces *blocking* artifacts due to inter-block discontinuities after quantization. H.265 employs a de-blocking filter on images inside the encoder

[2]https://x265.readthedocs.io/en/default/cli.html

loop which produces blurring, which is typically perceived as more desirable for human viewers than blocking. However, for biometric image compression, blurring some of the images is not desirable and the loop de-blocking filter should be turned off (*x265* offers the `--no-deblock` option to achieve this). Similarly, the sample adaptive offset (SAO) filter to sharpen the image after de-blocking is undesirable when compressing biometric images (the `--no-sao` option achieves this).

The compression strength or output video quality is controlled either by the quantization parameter (`--qp`) or by the constant rate factor (CRF, parameter `--crf`) / average bit rate control. The latter two techniques lead to the situation that the actual quantization parameter of different frames or even blocks within frames can vary strongly. For regular video material intended for human viewers, constant perceived quality is desirable. However, when compressing biometric images, the unequal distribution of the quantization error yields different comparison scores for different images or even regions within an image, which is undesired. *x265* writes Supplemental Enhancement Information (SEI) data to the compressed output videos to signal encoder versions and used parameters, *x265* does this for every key frame, introducing significant coding overhead. It is thus recommended to disable SEI entirely by using `--no-info`.

The trade-off between encoding speed and efficiency can be specified by a preset (parameter `--preset`) with 10 possible values ranging from `ultrafast` to `placebo`. Each preset sets a large number of other parameters at once[3]. While the default preset is `medium` we set to `placebo` in order to maximally exploit coding gain. Like presets, tunings (parameter `--tune`) set multiple other parameters at once to achieve a goal, e.g., fast decoding. By default, no tuning is specified and multiple so-called psycho-visual and perceptual quality optimizations are enabled. While this is beneficial for regular video material, it makes the comparison of different bit rates for biometric material unfair with potentially counter-intuitive results. For proper comparisons, either the `psnr` (or the `ssim`) tuning should be used.

In the experiments, we compare a "naive" setting, where default parameters are used in encoding and decoding, and a "recommended" setting, in which the parameters adapted to the biometric sample compression task, displayed in Table I, are employed.

Fig. 1 shows the comparison between naive and recommended (*recom*) settings for finger vein data as considered in [10] (in that earlier work only the naive setting was employed, the figures show results using a revised version of the recognition software as compared to [10]). The y-axis displays equal error rate (EER) determined by applying the FVC2004 protocol to the samples compressed to the compression ratio shown on the x-axis.

We clearly observe that (i) intra-frame compression techniques as suggested in ISO/IEC 19794-4 and ANSI/NIST-ITL 1-2007 (i.e. JPEG, JPEG2000) are not competitive to

[3]See https://x265.readthedocs.io/en/default/presets.html#presets for details.

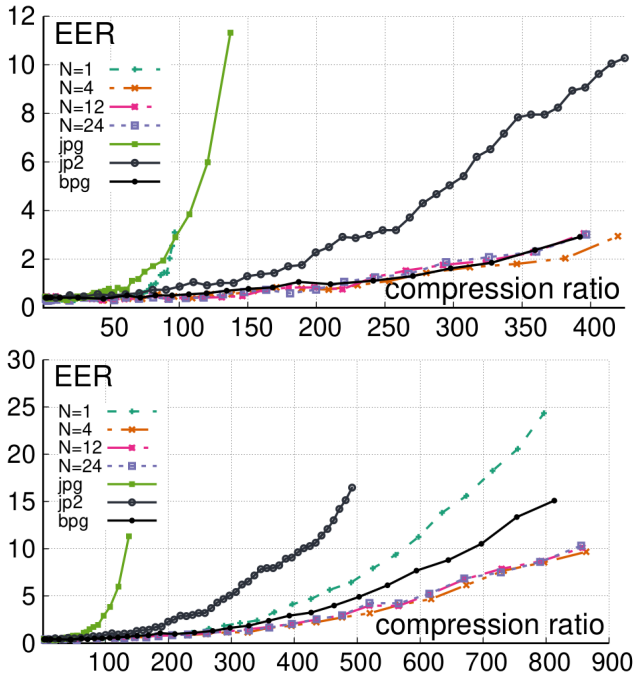

Fig. 1: naive vs. recom, UTFVP finger vein samples, *mc* recognition (compare [10] for earlier results)

the video-based compression and (ii) only the *recom* settings lead to compression results improving over intra-frame BPG compression (i.e. *recom* settings lead to better recognition results as compared to *naive* ones). Thus we observe that H.265 parameter settings as discussed can make a big difference, at least for finger vein samples as shown in this example. But what about fingerprints ?

D. Biometric quality driven assessement

In the FVC2004 test procedure, to compute non-mated sample scores, only the first sample of each finger is compared against the corresponding first sample of the same finger of all remaining individuals (to limit computational costs and to better balance the number of comparisons conducted for mated and non-mated sample scores). Thus, if $M = N$ or $M = kN$, the samples considered for computing the non-mated scores are always I-frames. As for the naive H.265 parameter settings P as well as B-frames exhibit worse quality as compared to I-frames, this disadvantage as compared to the *recom* setting might be hidden by relying on the FVC2004 test procedure. For this reason, besides assessing EER (FNMR and FMR) arising during recognition, we aim to also assess and compare the biometric quality of the compressed samples. In [21], [22] biometric quality metrics for fingerprints are surveyed and compared. We will focus on the two most popular metrics, i.e. NFIQ1 and NFIQ2. While NFIQ2 improves over NFIQ1 in many aspects, its behaviour with respect to compressed data seems to be problematic. For increasing moderate compression, NFIQ2 values randomly increase or decrease, for stronger compression, NFIQ2 values are said

to increase [23] due to compression artefacts misinterpreted as fingerprint components (while increasing NFIQ2 values indicate higher quality in general). On the other hand, NFIQ1 is said to behave rather stable under moderate compression [24]. In order to verify these statements on our data, we have JPEG compressed imprints of the FVC2 dataset to a number of different compression ratios and show the resulting NFIQ1.0 and NFIQ2.1 values of two instances in Table II. NFIQ2 indeed exhibits erratic behaviour in that the values increase for increasing compression strength up to some peak or plateau, only for strong compression NFIQ2 values decrease again and finally end up below the values for the original fingerprints for the highest compression ratio considered. On the other hand, NFIQ1 values behave rather stable and only exhibit higher values for strong compression (note that high NFIQ1 values indicate low quality in general). Therefore, we restrict our subsequent investigations to NFIQ1.0 results.

TABLE II: NFIQ1.0 values of two DB2 samples.

	orig.	cr9	cr11	cr13	cr17	cr28	cr49
Fingerprint sample 1_1							
NFIQ1.0	2	2	2	2	2	2	2
NFIQ2.0	38	37	38	43	57	43	27
Fingerprint sample 3_7							
NFIQ1.0	1	1	1	1	1	1	3
NFIQ2.0	47	52	46	51	49	50	16

IV. Results

In the following figures, we again plot EER vs. compression ratio as we have done in Fig. 1 for finger vein data. For all fingerprint datasets, it is obvious that both JPEG and JPEG2000 are not competitive as compared to the video-based compression schemes. However, in further aspects achieved results do differ in terms of the underlying datasets. For DB1 and DB3 (not shown in plots), H.265 results do not improve over BPG and there are hardly differences between the naive and recom settings, respectively. On the other hand, Fig. 2 compares the two compression settings when applying NBIS recognition to DB2. For both settings, H.265 results improve over BPG, for the recom setting even clearer and for $M = 2, 8, 32$ while in the naive setting results are worse than BPG for $M = 2$ for higher compression ratios (note that $N = 8$ for the FVC datasets).

Note also that H.265 with $M = 1$ delivers reasonable results comparable to BPG for the recom setting only (the SEI data overhead is too significant in the naive setting). Compression ratios higher than 180 cannot be achieved with BPG, however, given the high EER observed at this strong compression, this is hardly relevant in practice.

Fig. 3 displays the analogous results when applying VF recognition. The results and effects observed are almost identical, of course the observed EERs are at a much lower level overall. For the DB4 dataset (not shown in the plots), results are almost identical to DB2, only that in the naive setting for both recognition schemes H.265 is superior to BPG only for $M = 32$ (while again superior for the recom setting for $M = 2, 8, 32$ as in the DB2 case above).

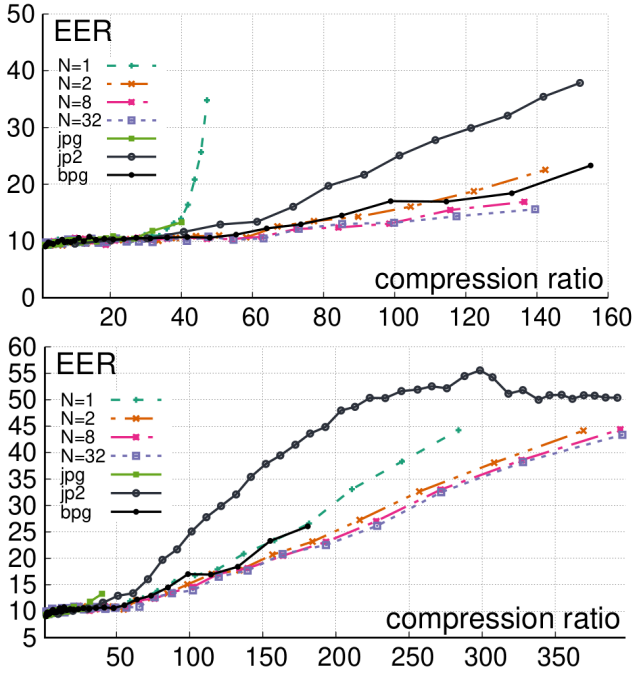

Fig. 2: naive vs. recom, NBIS recognition on DB2.

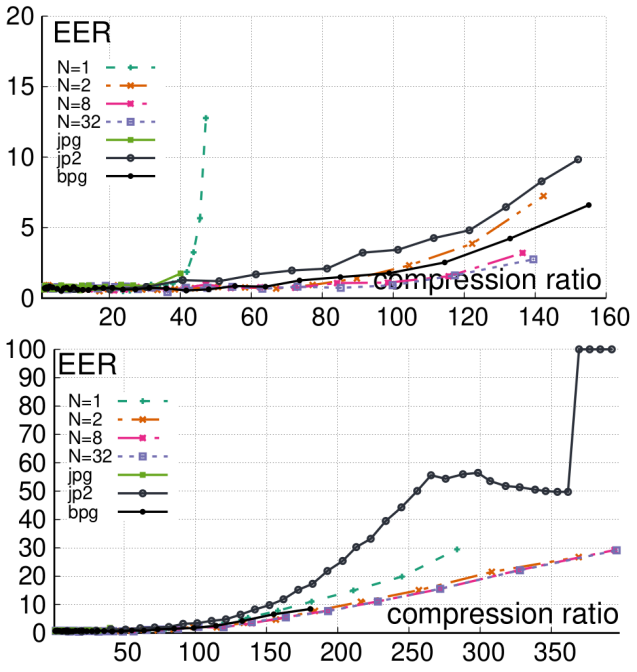

Fig. 3: naive vs. recom, VF recognition on DB2.

Finally, we want to demonstrate selected NFIQ1.0 results. Table III displays three exemplary parameter configurations for the DB2 data, always comparing the naive to the recom setting. Compression ratios are either equal or higher for the recom setting, the resulting average NFIQ1.0 values (averaged over 80 frames, i.e. samples of 10 fingers) are either equal or lower for the recom setting, again illustrating the better compression

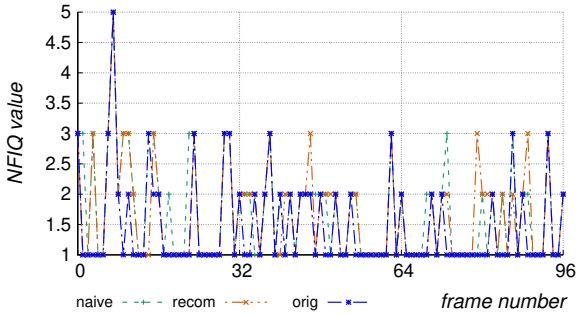

Fig. 4: DB1, naive vs. recom: comp.ratio = 185 vs. 186, ø NFIQ1.0 = 1.65 vs. 1.64, orig. ø NFIQ1.0 = 1.48.

behaviour of the latter.

TABLE III: DB2, $GOP = M = 8$.

comp.ratio		NFIQ1.0		
naive	recom	ø naive	ø recom	ø orig.
16.44	27.55	2.44	2.43	2.44
73.01	76.11	2.59	2.49	2.44
193.20	193.22	3.06	2.94	2.44

In Fig. 4 we display the individual NFIQ1.0 values of the first 96 frames (i.e. 12 fingers) of the DB1 dataset, where also a slight superiority of the recom setting can be detected (which cannot be seen in the EER results). In particular, we are able to observe the "downgrade" (in terms of NFIQ1.0 values) of certain frames under compression as compared to the uncompressed original frames.

V. Conclusion

Given the high variability among the samples of the FVC2004 data it may seem surprising that we are able to successfully apply fingerprint multi-sample compression, given the corresponding success on finger vein and iris sample data it is not really. While H.265 based multi-sample compression is not superior to BPG on all FVC2004 datasets, worse results compared to BPG are never obtained either. The x265 video en- and decoding parameters optimised lead to improved results as compared to default settings, so overall the proposed approach can be rated as being sensible.

However, some restrictions might not be compatible with a target application. First, the computational cost of the x265 based (encoding) approach is much higher as compared to e.g. BPG (caused by motion compensation). Second, access delay to arbitrary samples can be significant as compared to single sample systems (like BPG), in particular in case macro-blocks of a target sample are encoded in B-frame mode mostly.

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