

Automated Quality Assessment for Compressed Vibrotactile Signals Using Multi-Method Assessment Fusion

Andreas Noll^{1,3}, Markus Hofbauer¹, Evelyn Muschter^{2,3}, Shu-Chen Li^{2,3}, and Ekehard Steinbach^{1,3},

Abstract—Design and optimization of vibrotactile codecs require precise measurements of the compressed signals’ perceptual quality. In this paper, we present two computational approaches for estimating vibrotactile signal quality. First, we propose a novel full-reference vibrotactile quality metric called Spectral Perceptual Quality Index (SPQI), which computes a similarity score based on a computed perceptually weighted error measure. Second, we use the concept of Multi-Method Assessment Fusion (MAF) to predict the subjective quality. MAF uses a Support Vector Machine regressor to fuse multiple elementary metrics into a final quality score, which preserves the strengths of the individual metrics. We evaluate both proposed quality assessment methods on an extended subjective dataset, which we introduce as part of this work. For two of three tested vibrotactile codecs, the MSE between subjective ratings and the SPQI is reduced by 64% and 92%, respectively compared to the state of the art. With our MAF approach, we obtain the only currently available metric that accurately predicts real human user experiments for all three tested codecs. The MAF estimations reduce the average MSE to the subjective ratings over all three tested codecs by 59% compared to the best performing elementary metric.

I. INTRODUCTION

Quality assessment methods are widely used in audio and video compression algorithm development. In the context of haptic codec development, quality assessment methods are equally important to guarantee high fidelity signals [1]. Concerning the tactile domain, the ongoing standardization efforts for Tactile Internet and haptic codecs [2] have come to fruition in vibrotactile codec proposals such as [3]–[5], which allow for compressing vibrotactile signals in a similar way as acoustic and visual signals. A major goal of these efforts is to deliver tactile experiences over communication networks with the best possible perceptual quality. This requires accurately and effectively measuring the perceptual quality. Thus, considering the human perceptual limitations in the process is essential [6], [7].

*Funded by the German Research Foundation (DFG, Deutsche Forschungsgemeinschaft) as part of Germany’s Excellence Strategy – EXC 2050/1 – Project ID 390696704 – Cluster of Excellence “Centre for Tactile Internet with Human-in-the-Loop” (CeTI) of Technische Universität Dresden.

¹Department of Electrical and Computer Engineering and Munich Institute of Robotics and Machine Intelligence (MIRMI), Technical University of Munich, 80333 Munich, Germany, e-mail: {andreas.noll,markus.hofbauer,ekehard.steinbach}@tum.de.

²Chair of Lifespan Developmental Neuroscience, Technische Universität Dresden, 01062 Dresden, Germany, e-mail: {evelyn.muschter, shu-chen.li}@tu-dresden.de

³Centre for Tactile Internet with Human-in-the-Loop (CeTI), Technische Universität Dresden, 01062 Dresden, Germany.

A. Noll and M. Hofbauer contributed equally to this work.

So far, perceptual quality in the tactile domain has mainly been measured with human experimental procedures [8]. However, these experiments are time-consuming and require recruiting many participants. Ultimately, the goal is to avoid human assessment studies by using computable perceptual quality metrics. Similar to other domains, the use of different compression techniques results in different types of coding artifacts. This in turn leads to different performances of elementary quality metrics with their own strengths and weaknesses. The current perceptual metrics are unable to reflect the human experimental results consistently.

In this paper, we address this problem by proposing two new methods. First, we propose a novel full-reference vibrotactile quality metric called Spectral Perceptual Quality Index (SPQI). SPQI uses the absolute threshold of vibrotactile perception to compute a perceptual error measure. This error measure is then mapped to a score strictly between 0 and 1 to reflect a similarity rating closely related to human user studies [8]. Second, we use Multi-Method Assessment Fusion (MAF) to combine multiple quality metrics. Our MAF approach, called Vibrotactile Multi-Method Assessment Fusion (VibroMAF), is inspired by Video Multi-Method Assessment Fusion (VMAF) [9] and assigns weights to each elementary metric using a Support Vector Machine (SVM) to fuse the weighted quality measures into a final score. This allows for better preserving the strengths of the individual metrics. Additionally, we introduce a new dataset with subjective quality ratings for training and evaluating the proposed metrics.

In summary, we have the following main contributions:

- We introduce a new dataset with subjective quality ratings for the vibrotactile codec from [3].
- We propose a novel perceptual vibrotactile quality metric called Spectral Perceptual Quality Index (SPQI).
- We adopt Multi-Method Assessment Fusion (MAF) to predict the subjective quality by a weighted combination of multiple individual quality metrics.

II. RELATED WORK

In the tactile domain, the three vibrotactile codecs described in [3]–[5], [11] represent the state of the art (Table I). The first codec named Vibrotactile Perceptual Codec using DWT and SPIHT (VPC-DS) was introduced in [5]. It uses a DWT, quantization and the SPIHT algorithm together with a psychohaptic model, which steers the quantization to compress signals with minimal perceptual impairments. Therefore, impairments are mostly introduced in frequency ranges where they are not perceivable. The second codec

VC-PWQ	Vibrotactile Codec with Perceptual Wavelet Quantization [3]
PVC-SLP	Perceptual Vibrotactile Codec with Sparse Linear Prediction [4]
VPC-DS	Vibrotactile Perceptual Codec using DWT and SPIHT [5]
ST-SIM	Spectral-Temporal SIMilarity [10]
SPQI	Spectral Perceptual Quality Index
VibroMAF	Vibrotactile Multi-Method Assessment Fusion
PC	Pearson Correlation
MSE	Mean Squared Error

TABLE I: Overview of the acronyms for the relevant codecs, perceptual metrics and performance criteria.

named Perceptual Vibrotactile Codec with Sparse Linear Prediction (PVC-SLP) [4] employs linear prediction with a sparsity constraint to decompose the input signal into coefficients and a residual. These coefficients and the residual are then quantized independently. A so-called acceleration sensitivity function, derived from the absolute threshold of perception, quantizes the residual. The third codec named Vibrotactile Codec with Perceptual Wavelet Quantization (VC-PWQ) was introduced in [3] improving on the previous codec from [5]. Specifically, the psychohaptic model was refined, the quantization model was changed to preserve more information and an added arithmetic coding stage served to achieve higher compression.

So far, one relevant perceptual metric for vibrotactile signals has been introduced, named the Spectral-Temporal SIMilarity (ST-SIM) [10]. It uses spectral and temporal properties of compressed signals to compute a score between 0 and 1. First, the absolute threshold is subtracted from the spectra of original and compressed signals and the results are then mapped to a range between 0 and 1 using a sigmoid function. Then, the overlap between the two resulting functions is calculated. This operation examines only the overlap of perceivable frequencies and not the exact difference. In time domain, the similarity score between two signals is calculated through a formula similar to Pearson Correlation (PC). The time component of this metric is therefore not perceptual. Finally, spectral and temporal scores are combined through weighted multiplication. An empirically selected parameter determines how strongly the spectral and temporal scores are considered. As in previous work, in this paper we weigh the temporal score twice as strongly as the spectral score, which is supported by [12].

In [8], we presented a subjective assessment method based on perceptual similarity comparisons. The subjective assessment is performed by displaying a pair of original and compressed signal two times consecutively with different orderings (i.e. original signal, then compressed signal and the reverse) to human assessors. After that, the assessors are asked to rate the similarity of the compressed signal to the original signals on a scale from 0 to 10 with 10 as the highest similarity. High similarity implies high signal quality after compression here. The experiment includes a hidden reference and two anchor signals. The hidden reference resembles a catch trial in which the supposedly compressed signal is actually the original signal. This hidden reference should receive high ratings and assessors who rate this very low can be excluded in the post-screening step. The

anchor signals are signals containing controlled perceptual impairments. They serve to assess whether the rating scale is appropriate. Using this method, we recorded ratings for the PVC-SLP and VPC-DS codecs with 19 participants, which are also presented in [8].

The area of image and video processing already provides a large number of codecs and quality metrics with various configuration options. Depending on the video content, individual quality metrics perform differently with respective strengths and weaknesses. To achieve a meaningful performance for a wide range of video contents and codecs, fusion-based quality assessment methods such as Fusion-based Video Quality Assessment index [13] and Ensemble-learning-based Video Quality Assessment index [14] allow for compensating the weaknesses of individual metrics. Together with Netflix, the authors of [13], [14] proposed Video Multi-Method Assessment Fusion (VMAF) [9] to estimate the subjective quality. VMAF combines the strengths of multiple elementary video quality metrics such as Peak Signal-to-Noise Ratio, Structural Similarity Index, etc. by fusing the individual metric scores using a SVM regressor. This approach achieves more accurate results than traditional methods and has become the defacto standard for video quality assessment [15]. In this work, we follow the idea of VMAF by fusing multiple elementary vibrotactile quality metrics.

III. SUBJECTIVE EVALUATION DATA

In this section, we introduce a new dataset with subjective quality ratings of vibrotactile signals compressed by the VC-PWQ codec [3]. Using the assessment method from [8], which is largely based on MUSHRA from the audio domain [16], we measured ratings with ten human participants between 20 and 65 years old. All participants reported as healthy with normal tactile perception capabilities.

For the assessment, we selected the same 8 signals (4 materials, recorded with the 3x3 tooltip, *fast* and *slower* speeds) as in [8] from the database of [17]. As described in [8], these materials, *aluminium grid* (Signal IDs: 117, 120), *cork* (Signal IDs: 133, 136), *polyester pad* (Signal IDs: 146, 149) and *rubber* (Signal IDs: 150, 153), are chosen since they cover a broad range of vibrotactile signal characteristics from the 280-signal database. The ratings are measured at nine different compression ratios (CRs), namely 5, 10, 15, 20, 25, 30, 35, 40 and 45.

To enable a comparison to the previously published data in [8], we normalize all ratings using the hidden reference. In theory, the hidden reference should receive a rating of 10 since it is exactly equal to the original signal. In reality the mean rating for the hidden reference signal is around 8.5 to 9. In our data, we also observe that there is almost no mean rating above that of the hidden reference. Thus, we normalize all ratings for each signal individually by dividing through the mean rating of the corresponding hidden reference. Thus, the range of these normalized ratings is now between 0 and 1. We can justify this normalization with the fact that if a signal receives a similar rating as the hidden reference, it can

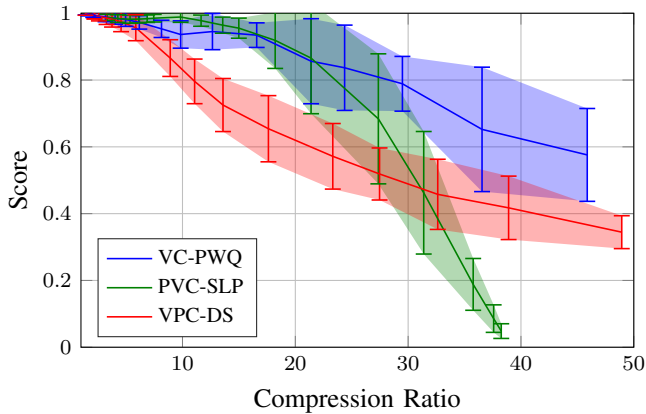


Fig. 1: Average quality score of the normalized and interpolated subjective quality ratings for the three vibrotactile codecs VC-PWQ, PVC-SLP, and VPC-DS.

be regarded as perceptually equal to the original signal and should therefore receive the highest possible rating.

The ratings for all signals are measured for 6 different CRs for the PVC-SLP and VPC-DS in [8]. For the VC-PWQ, we measure ratings at 9 different CRs. Originally available were 17 different CR levels for all codecs [3]–[5]. Thus, to make direct comparison of computed metrics and ratings possible, rating data needs to be available for the 17 original CRs. In short, the 6 or 9 CRs of each signal are a subset of these original 17 CRs. This means, we can acquire the rating data for all CRs by interpolating the measurements from the 6 or 9 onto the 17 CRs. To do this interpolation, we use the `interp1` function in MATLAB and interpolate the rating measurements for each signal individually. The specific interpolation method used is `makima`, which is similar to `spline` but has significantly less over- and undershoots on the edges. We verify that the interpolation causes no visible difference in ratings by visual inspection.

Fig. 1 visualizes the normalized and interpolated subjective quality ratings for the three vibrotactile codecs VC-PWQ, PVC-SLP, and VPC-DS. We show the mean curves over all eight signals and the standard deviation interval. We observe that the VC-PWQ now matches the performance of PVC-SLP for lower CRs, while for higher CRs the VC-PWQ is the best choice. The new measurements show slightly more variation over the CR, which we attribute to the fact that we have fewer human subjects for these ratings.

IV. SPECTRAL PERCEPTUAL QUALITY INDEX

We propose a novel full-reference perceptual metric called *Spectral Perceptual Quality Index (SPQI)* that is able to reflect real-life experimental results accurately. Our goal is to avoid some of the shortcomings of existing metrics and produce more accurate results.

Fig. 2 depicts the process of computing the SPQI. To compute the SPQI of a compressed signal $c[n]$ with respect

to its original signal $s[n]$, we first divide the signals into blocks $c_i[n]$ and $s_i[n]$. The blocks are transformed with a DCT transform to obtain $S_i[m]$ and $C_i[m]$, respectively.

We first subtract the absolute threshold of perception $T[m]$ from $S_i[m]$ and $C_i[m]$. This threshold is calculated as a function of frequency as described in [3]. This subtraction in dB is a filtering operation, where the most perceivable parts of each block are amplified. We receive the perceptually weighted spectra $S_{w,i}[m]$ and $C_{w,i}[m]$, which are transformed from dB to power. These two weighted spectra are then subtracted from each other. This gives us a perceptually weighted difference spectrum. Then, we calculate the sum of all absolute values of the resulting difference spectrum and normalize by the sum of the absolute values of $S_{w,i}[m]$. Since we have a power spectrum, the summation of all values corresponds to the calculation of the energy of the difference spectrum. After that we transform back to the dB domain.

The resulting value $e_{p,i}$ can be regarded as a measure for the perceptual error, as it resembles a perceptually weighted, normalized Mean Squared Error (MSE). In contrast to an objective error measure, it contains information on the perceptual relevance of the error, which was introduced into the compressed signal.

We assume that humans tolerate a certain amount of this perceptual error up to some threshold before it becomes noticeable. This means that for a low value of $e_{p,i}$ the SPQI should be close to 1 since perceptual signal quality is high. Conversely, for $e_{p,i}$ being high, the SPQI should be close to 0, since a high perceptual error means low signal quality. In between, the SPQI value should be declining around the threshold value τ . A mapping from $e_{p,i}$ to an SPQI score that has the described properties is

$$\text{SPQI}_i = \frac{1}{2}(1 - \tanh(\eta(e_{p,i} - \tau))) =: \Xi(e_{p,i}). \quad (1)$$

Here, the parameter η controls the slope by which the SPQI declines around τ . To the best of our knowledge, no studies exist that would allow us to derive optimal values for τ and η . Thus, we aim to find close-to-optimal values for these two parameters by using the available data. We describe the derivation of these parameters in Section VI-B.

Finally, we receive the SPQI value SPQI_i for the i -th block. The SPQI of $c[n]$ is then calculated as the mean of SPQI_i over all i . This enables us to accurately measure the vibrotactile signal quality reflecting human perception.

V. MULTI-METHOD ASSESSMENT FUSION

Next, we propose a Multi-Method Assessment Fusion (MAF) approach for predicting the subjective quality called VibroMAF. VibroMAF is inspired by VMAF [9], which is the defacto standard for video quality assessment [15]. We follow the idea of VMAF by fusing multiple elementary vibrotactile quality metrics.

Every individual metric has its own strengths and weaknesses, depending on the source signal, the employed codec, or the degree of distortion. Fusing the individual metrics into a final score combines the strengths of all input metrics.

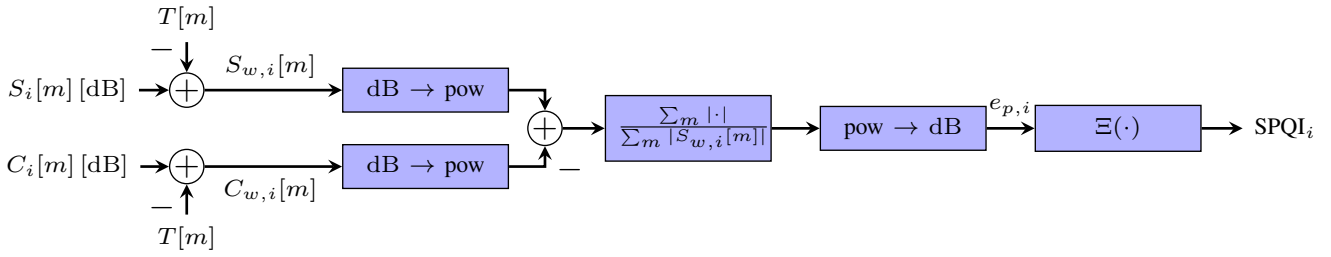


Fig. 2: SPQI computation process.

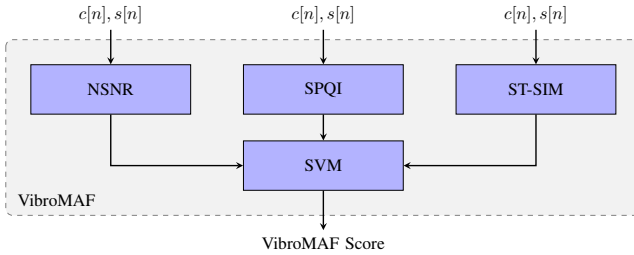


Fig. 3: Workflow of the proposed VibroMAF. The SVM regressor determines the weight for each individual metric score calculated from the compressed signal $c[n]$ and original signal $s[n]$.

Similar to VMAF, we train a Support Vector Machine (SVM) regressor to assign weights to the elementary metrics and fuse them into a single quality score.

Fig. 3 visualizes the workflow of the proposed SVM based metric fusion. VibroMAF considers the Normalized Signal-to-Noise Ratio (NSNR), the ST-SIM, and the proposed SPQI as input for the SVM. The NSNR is calculated by normalizing all SNR values by 75 dB and restricting the output to the range of 0 to 1. The SVM combines the weighted metric scores into a final output. This results in an accurate and comparable estimation of the signal quality and allows for extending MAF with future elementary quality metrics to further improve the estimation.

VI. EVALUATION AND RESULTS

In this section, we define the performance evaluation criteria, discuss the experiments conducted to evaluate the proposed approaches and present the results.

A. Performance Criteria

We first define the premise on which we evaluate the suitability of perceptual metrics. We measure the MSE and PC of the estimated quality scores compared to the scores of the subjective experiments. We compute the two measures using the ratings for all eight signals rather than just the overall mean rating.

The PC provides insights how well the computed metric values correlate with the real ratings. This is important because in quality assessment, we often are evaluating quality by comparing. Therefore, we are interested to know if the metric can discern differences in perceptual quality between codecs and different CRs.

Metric	VC-PWQ [3]	PVC-SLP [4]	VPC-DS [5]
min MSE SPQI	0.006	0.028	0.005
MSE ST-SIM [10]	0.017	0.009	0.064
max PC SPQI	0.843	0.876	0.960
PC ST-SIM [10]	0.837	0.964	0.921

TABLE II: Performance comparison of SPQI and ST-SIM for the vibrotactile codecs VC-PWQ, PVC-SLP, and VPC-DS.

The MSE determines how close the metric values are to the ratings. Intuitively, the best metric is the one that provides scores that are equal to the experimental ratings. Thus, we seek to achieve the smallest possible MSE.

B. SPQI

We evaluate the SPQI on the dataset of 8 signals described in Section III by computing the PC and MSE as described in Section VI-A. We do so by varying the parameters τ between -5 dB and 0 dB with steps of 0.1 dB and η between 0 and 1 with steps of 0.05 . The block length is 512 samples. Fig. 4 shows the resulting MSEs and PCs for all three codecs.

First, we see that the results for VC-PWQ and VPC-DS are similar, whereas PVC-SLP leads to a different outcome. In order to assess, whether the SPQI can outperform the ST-SIM, we compute the minimum MSE and maximum PC values over η and τ of the SPQI for all three codecs in Table II. Comparing to the values of ST-SIM, we can see that for the PVC-SLP the SPQI never achieves the performance of ST-SIM. For the other two codecs however, it is possible to achieve substantially better ratings with the SPQI.

To find the close-to-optimal set of parameters, we optimize jointly for the VC-PWQ and VPC-DS. This is justified since the plots in Fig. 4 for these two codecs are highly similar. Maximizing the PC gives us $\tau = -3.1$ dB and $\eta = 0.4$. However, for these values the MSE is poor with 0.018 and 0.014 for the VC-PWQ and VPC-DS, respectively. Minimizing the MSE results in $\tau = -2.0$ dB and $\eta = 0.3$. Using those parameters minimizes the MSE of VC-PWQ and VPC-DS to 0.007 and 0.006 , respectively. We achieve a PC of 0.839 for VC-PWQ and 0.960 for VPC-DS. Thus, we see that the PC is almost at the maximum value. Fig. 4 depicts the chosen values of τ and η in red points.

In Fig. 5, we show the resulting mean curves of the ratings from Fig. 1, the SPQI, and ST-SIM for all eight signals. For

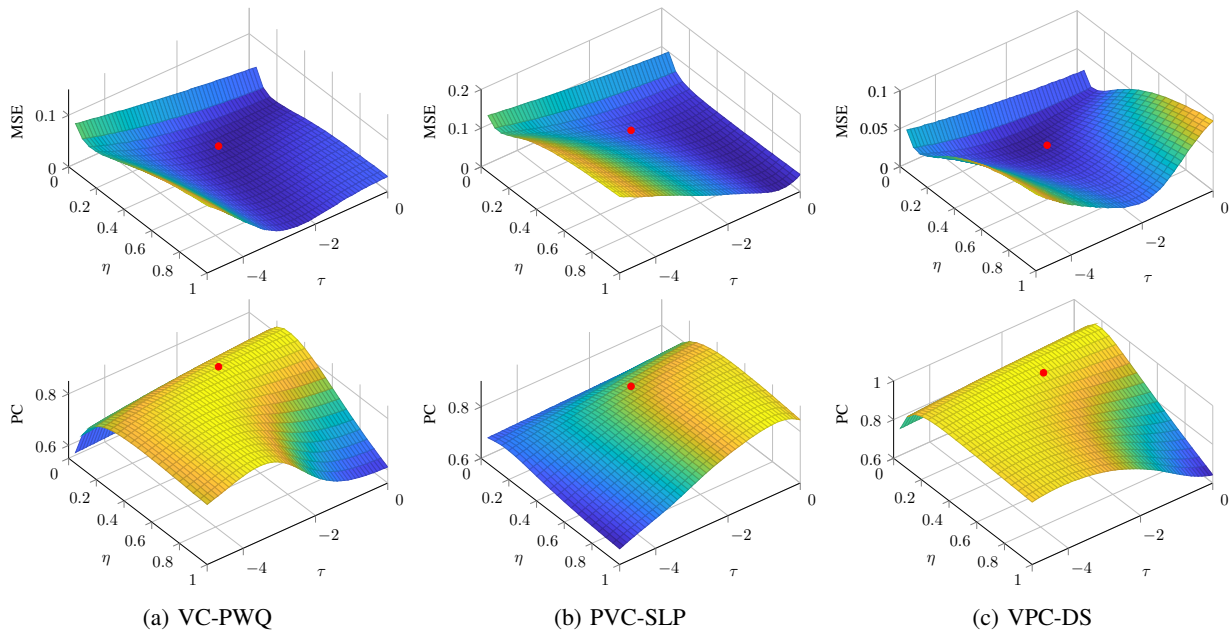


Fig. 4: MSE (first row) and PC (second row) as a function of τ and η for the three examined vibrotactile codecs averaged over all test signals. The red dot highlights the chosen values of $\eta = 0.3$ and $\tau = -2.0$.

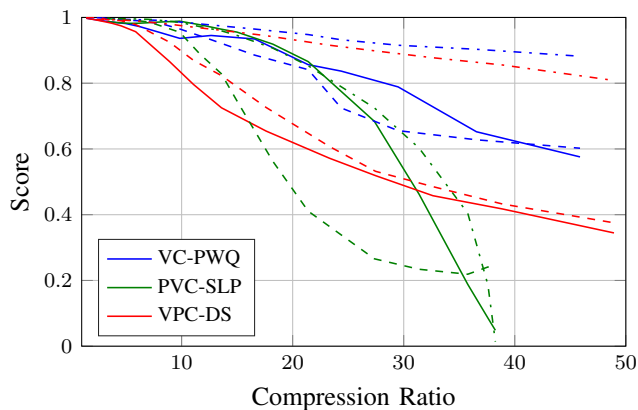


Fig. 5: Comparison of the SPQI (dashed) and ST-SIM (dash-dotted) to the subjective ratings (solid) for the three vibrotactile codecs VC-PWQ, PVC-SLP, and VPC-DS

the PVC-SLP, the ST-SIM matches the ratings closer, while for the VC-PWQ and VPC-DS our new SPQI is superior.

C. VibroMAF

We train the SVM using the dataset with subjective ratings introduced in Section III. We select six of the eight signals for training and two remain for testing. The two test signals selected are *aluminium grid - fast* (120) and *polyester pad - slower* (149) as representative test signals of different material classes and recording speeds. We configure the SVM regressor with a Radial Basis Function kernel, a regularization parameter of 3000, and an epsilon of 0.1. All configurations we used were determined empirically.

We evaluate the performance of VibroMAF on the two

Metric	All Codecs	VC-PWQ [3]	PVC-SLP [4]	VPC-DS [5]
MSE VibroMAF	0.011	0.007	0.019	0.006
MSE SPQI	0.027	0.009	0.067	0.006
MSE ST-SIM [10]	0.037	0.019	0.012	0.080
MSE NSNR	0.440	0.452	0.526	0.341
PC VibroMAF	0.918	0.854	0.901	0.957
PC SPQI	0.800	0.807	0.741	0.982
PC ST-SIM [10]	0.775	0.831	0.945	0.918
PC NSNR	0.453	0.433	0.739	0.536

TABLE III: Performance comparison of VibroMAF with the elementary quality metrics SPQI, ST-SIM, and NSNR for the vibrotactile codecs VC-PWQ, PVC-SLP, and VPC-DS.

test signals with subjective ratings. We encode the signals at different quality levels with the vibrotactile codecs VC-PWQ, PVC-SLP, and VPC-DS. We measure the MSE and PC of VibroMAF and the elementary quality metrics SPQI, ST-SIM, and NSNR. Table III summarizes the resulting quality scores for the individual codecs and the average of all codecs.

On average, VibroMAF performs best with an MSE of 0.011 and a PC of 0.915. For the individual codecs, VibroMAF shows the best performance on VC-PWQ for both MSE and PC. The proposed elementary metric SPQI shows together with VibroMAF the lowest MSE for the VPC-DS codec and the highest PC for this codec. For the PVC-SLP codec, the ST-SIM achieves the best performance in terms of MSE and PC. Notably, the MSE of the NSNR is significantly higher than the other metrics.

While VibroMAF does not outperform ST-SIM for the PVC-SLP codec, it benefits from the strengths of the other metrics and hence shows the best performance on average.

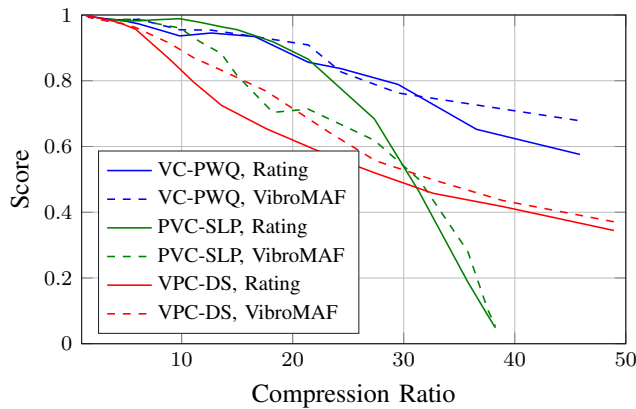


Fig. 6: VibroMAF score compared to subjective ratings for the vibrotactile codecs VC-PWQ, PVC-SLP, and VPC-DS.

Fig. 6 visualizes the VibroMAF scores estimated and the subjective ratings for the individual codecs highlighting the precise matches for all codecs. Contrarily, the performance of the elementary metrics is highly correlated to the selected codec. A possible explanation for the strong performance of the metric-encoder pairs (VC-PWQ, SPQI) and (PVC-SLP, ST-SIM) is that the metrics represent the strengths of the respective codec. This demonstrates the ability of VibroMAF to combine the strengths of all individual metrics. Further, it enables a better comparability among the signal qualities of different codecs. Additionally, VibroMAF can be further improved with future quality metrics and vibrotactile codecs.

VII. CONCLUSION

In this paper, we proposed the novel metric SPQI to accurately estimate the perceptual quality of compressed vibrotactile signals. The SPQI computes the perceptually weighted error measure and maps this error measure to a similarity score between 0 and 1. Inspired by VMAF, we developed the fusion method VibroMAF which combines multiple elementary vibrotactile quality metrics. This allows for combining the strengths of multiple elementary metrics. We used a SVM to fuse the individual scores of SPQI, ST-SIM, and NSNR into a final quality estimation. Additionally, we introduced a new dataset with subjective ratings of vibrotactile signals which was used for training and the evaluation of the proposed metrics.

With the SPQI, we reduced the MSE between the subjective ratings and the computed metric by 64% and 92% compared to the state of the art for two of the three latest vibrotactile codecs, while for the third codec ST-SIM is superior. With VibroMAF we reduce the average MSE to the subjective ratings over all three codecs by 59% compared to best performing elementary metric.

While VibroMAF does not outperform all elementary metrics for all vibrotactile codecs, the results demonstrate that fusing individual metric scores allows for compensating weaknesses of the elementary metrics for certain codecs. Further, VibroMAF is well suited for generating accurate and comparable quality ratings across all three codecs. For future

work, VibroMAF is extendable with new vibrotactile quality metrics to further increase the resulting accuracy. We provide VibroMAF as well as the elementary metrics as Open Source Python implementation available on GitHub¹ for a simple usage and extension with future metrics.

REFERENCES

- [1] E. Steinbach, S. Hirche, M. Ernst, F. Brandi, R. Chaudhari, J. Kammerl, and I. Vittorias, "Haptic communications," *Proceedings of the IEEE*, vol. 100, no. 4, pp. 937–956, 2012.
- [2] E. Steinbach, M. Strese, M. Eid, X. Liu, A. Bhardwaj, Q. Liu, M. Al-Ja'afreh, T. Mahmoodi, R. Hassen, A. El Saddik *et al.*, "Haptic codecs for the tactile internet," *Proceedings of the IEEE*, vol. 107, no. 2, pp. 447–470, 2018.
- [3] A. Noll, L. Nockenberger, B. Gülecüyüz, and E. Steinbach, "Vc-pwq: Vibrotactile signal compression based on perceptual wavelet quantization," in *2021 IEEE World Haptics Conference (WHC)*. IEEE, 2021, pp. 427–432.
- [4] R. Hassen, B. Guelecüyez, and E. G. Steinbach, "Pvc-slp: Perceptual vibrotactile-signal compression based-on sparse linear prediction," *IEEE Transactions on Multimedia*, 2020.
- [5] A. Noll, B. Gülecüyüz, A. Hofmann, and E. Steinbach, "A rate-scalable perceptual wavelet-based vibrotactile codec," in *2020 IEEE Haptics Symposium (HAPTICS)*. IEEE, 2020, pp. 854–859.
- [6] T. L. Senkow, N. D. Theis, J. C. Quindlen-Hotek, and V. H. Barocas, "Computational and psychophysical experiments on the pacinian corpuscle's ability to discriminate complex stimuli," *IEEE Transactions on Haptics*, vol. 12, no. 4, pp. 635–644, 2019.
- [7] S.-C. Li, E. Muschter, J. Limanowski, and A. Hatzipanayioti, "Chapter 9 - human perception and neurocognitive development across the lifespan," in *Tactile Internet*, F. H. Fitzek, S.-C. Li, S. Speidel, T. Strufe, M. Simsek, and M. Reisslein, Eds. Academic Press, 2021, pp. 199–221.
- [8] E. Muschter, A. Noll, J. Zhao, R. Hassen, M. Strese, B. Guelecüyez, S.-C. Li, and E. Steinbach, "Perceptual quality assessment of compressed vibrotactile signals through comparative judgment," *IEEE Transactions on Haptics*, 2021.
- [9] N. T. Blog, "Toward A Practical Perceptual Video Quality Metric," Jun. 2016. [Online]. Available: <https://netflixtechblog.com/toward-a-practical-perceptual-video-quality-metric-653f208b9652>
- [10] R. Hassen and E. Steinbach, "Subjective evaluation of the spectral temporal similarity (st-sim) measure for vibrotactile quality assessment," *IEEE Transactions on Haptics*, vol. 13, no. 1, pp. 25–31, 2020.
- [11] E. Steinbach, S.-C. Li, B. Gülecüyüz, R. Hassen, T. Hulin, L. Johannsmeier, E. Muschter, A. Noll, M. Panzirsch, H. Singh, and X. Xu, "Chapter 5 - haptic codecs for the tactile internet," in *Tactile Internet*, F. H. Fitzek, S.-C. Li, S. Speidel, T. Strufe, M. Simsek, and M. Reisslein, Eds. Academic Press, 2021, pp. 103–129.
- [12] L. A. Jones and N. B. Sarter, "Tactile displays: Guidance for their design and application," *Human factors*, vol. 50, no. 1, pp. 90–111, 2008.
- [13] J. Y. Lin, T.-J. Liu, E. C.-H. Wu, and C.-C. J. Kuo, "A fusion-based video quality assessment (fvqa) index," in *Signal and Information Processing Association Annual Summit and Conference (APSIPA), 2014 Asia-Pacific*, 2014, pp. 1–5.
- [14] J. Y. Lin, C.-H. Wu, I. Katsavounidis, Z. Li, A. Aaron, and C.-C. J. Kuo, "Evqa: An ensemble-learning-based video quality assessment index," in *2015 IEEE International Conference on Multimedia Expo Workshops (ICMEW)*, 2015, pp. 1–6.
- [15] N. T. Blog, "VMAF: The Journey Continues," Oct. 2018. [Online]. Available: <https://netflixtechblog.com/vmaf-the-journey-continues-44b51ee9ed12>
- [16] B. Series, "Method for the subjective assessment of intermediate quality level of audio systems," *International Telecommunication Union Radiocommunication Assembly*, 2014.
- [17] J. Kirsch, A. Noll, M. Strese, Q. Liu, and E. Steinbach, "A low-cost acquisition, display, and evaluation setup for tactile codec development," in *2018 IEEE International Symposium on Haptic, Audio and Visual Environments and Games (HAVE)*. IEEE, 2018, pp. 1–6.

¹<https://github.com/hofbi/vibromaf>