Using Texture Measures for Visual Quality Assessment

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***Abstract*—The automatic quality assessment of images and videos is a crucial problem for a wide range of applications in the fields of computer vision and multimedia processing. For instance, many computer vision applications, such as biometric identification, content retrieval, and object recognition, rely on input images with a specific range of quality. Therefore, a great research effort has been made to develop a visual quality assessment (VQA) methods that are able to automatically estimate quality. However, VQA still faces several challenges. In the case of images, most of the proposed methods are complex and require a reference (pristine image) to estimate the quality, which limits their use in several multimedia applications. For videos, the current state-of-the-art methods still perform worse than the methods designed for images, both in terms of prediction accuracy and computational complexity. In this work, we proposed a set of methods to estimate visual quality using texture descriptors and machine learning. Starting from the premise that visual impairments alter image and video texture statistics, we propose a framework that use these descriptors to produce new quality assessment methods, including no-reference (blind) and full-reference quality metrics. Experimental results indicate that the proposed metrics present a good performance when tested on several benchmark image and video quality databases, outperforming current state-of-the-art metrics.**

***Index Terms*—Visual quality, objective metrics, no-reference image quality assessment, video quality assessment**

I. Introduction

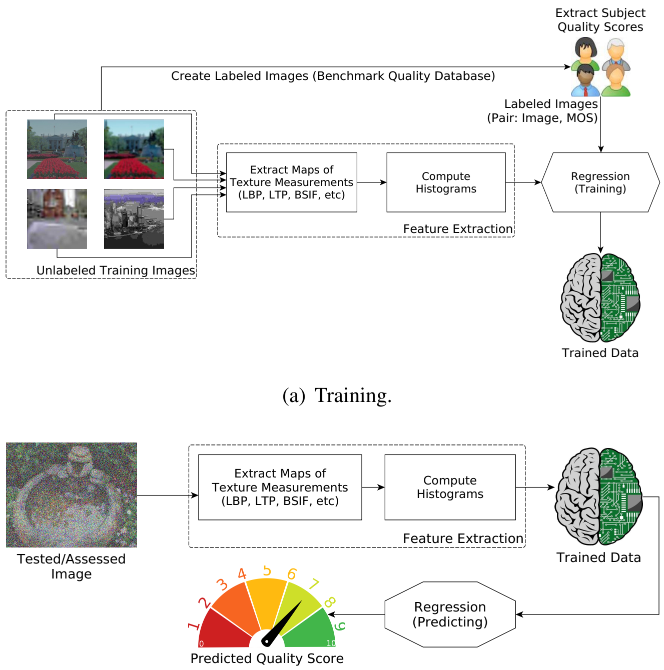
Visual quality assessment is an important problem in computer vision (CV). The quality of image and videos affects the performance of the several CV algorithms. For instance, Karahan *et al.* [1] have tested the performance of face recognition methods, based on deep convolutional neural networks (DCNN), for images with different levels of degradations. They observed that, although DCNN models are robust to color distortions, some structural distortions cause a significant decrease in performance. In addition to that, Dodge & Karam [2] demonstrated that DCNNs are susceptible to image quality distortions, particularly to blur and noise. More specifically, they inserted distortions into a dataset of images and tested the performance of identification algorithms that used different DCNN architectures. Bharadwaj *et al.* [3] investigated the effects of quality on the performance of biometric systems. Moreover, Kupyn *et al.* [4] have shown that object detection methods based on deep learning approaches [5], [6] are greatly affected by the quality of the input images, as illustrated in Fig. 1. Another examples of known CV algorithms that are affected by the quality of the input images include finger vein detection [7], video stream recognition systems [8], deep learning reconstruction of magnetic resonance imaging (MRI) [9], multi-view activity recognition [10], etc [11].

Fig. 1. Object detection using YOLO [5] on the distorted (left) and on the pristine (right) images from GoPro [6] dataset. The detection effectiveness of YOLO is remarkably impaired by the quality of the input image.

Additionally, due to the popularity of multimedia services over the Internet, the requirements of end users have changed in terms of the quality. In a recent report, Conviva®has shown that viewers are demanding a delivered multimedia content with a higher quality [12]. But, in the context of images and videos, higher quality content generally correspond to larger file sizes, which implies in higher network traffic and storage space. This growing network traffic and storage space, as pointed out by Cisco®[13], is mostly composed of multimedia content. Since the quality of the multimedia content can be altered in any stage of the multimedia communication chain, such as capture, compression, transmission, reproduction, and display, it is important to design automatic tools that are able to predict the quality of the visual stimuli perceived by the user. In other words, techniques for assessing the quality of image and video signals are crucial for most multimedia applications.

Notwithstanding, the design of automatic methods that estimate the quality of a multimedia content is a challenging problem, which requires solving three major issues. The first one is to determine a set of features that are relevant to visual quality. The second is to establish a pooling strategy for assessing visual quality over space and time. The third problem is how to create a model for mapping the pooled data

*This work is summary of a Ph.D. dissertation developed in the University of Brasília.



(a) Training.

(b) Predicting.

Fig. 2. Stages of the proposed no-reference image quality metric.

into estimates of the subjective quality scores. Hemami and Reibman [14] have named these three problems as measuring, pooling, and mapping, respectively. Measuring refers to the computation of the stimuli physical quantities. Pooling refers to the combination of the measurements, over a suitable subspace, to represent the quality of the stimuli. Mapping corresponds to modeling the result of the pooling into an estimate of subjective scores.

In this work, we investigate the use of texture measures (or descriptors) in image and video quality assessment methodologies. We chose to adopt a feature-based approach because this type of approach does not require assumptions about what types of artifacts (degradations) are present in the stimuli or its semantic content. For this reason, the chosen approach is more general and can be more widely used in multimedia applications. Feature-based approaches can be divided into Natural scene statistics (NSS) and Machine Learning (ML) approaches. NSS approaches are based on the hypothesis that the statistical properties of natural scenes are affected by distortions or artifacts. ML approaches, on the other hand, relies on a large number of features that are designed to capture relevant factors affecting visual quality. Since visual features are not easily interpreted, choosing them is one of the main challenges in this type of approach. In this work, we choose an ML approach because it provides a superior performance when compared to other approaches.

This document summarizes the main contents of the Ph.D. dissertation entitled “Using Texture Measures for Visual Quality Assessment”, which was developed in the Department of Computer Science of the University of Brasília. In Section II, we explain the texture measurement adopted in this work. Sections III and IV describe the application of texture measures for assessing image and video, respectively. The conclusions are presented in Section V. Finally, we summarize the accomplishments of this research in Section VI.

II. Texture Measurements

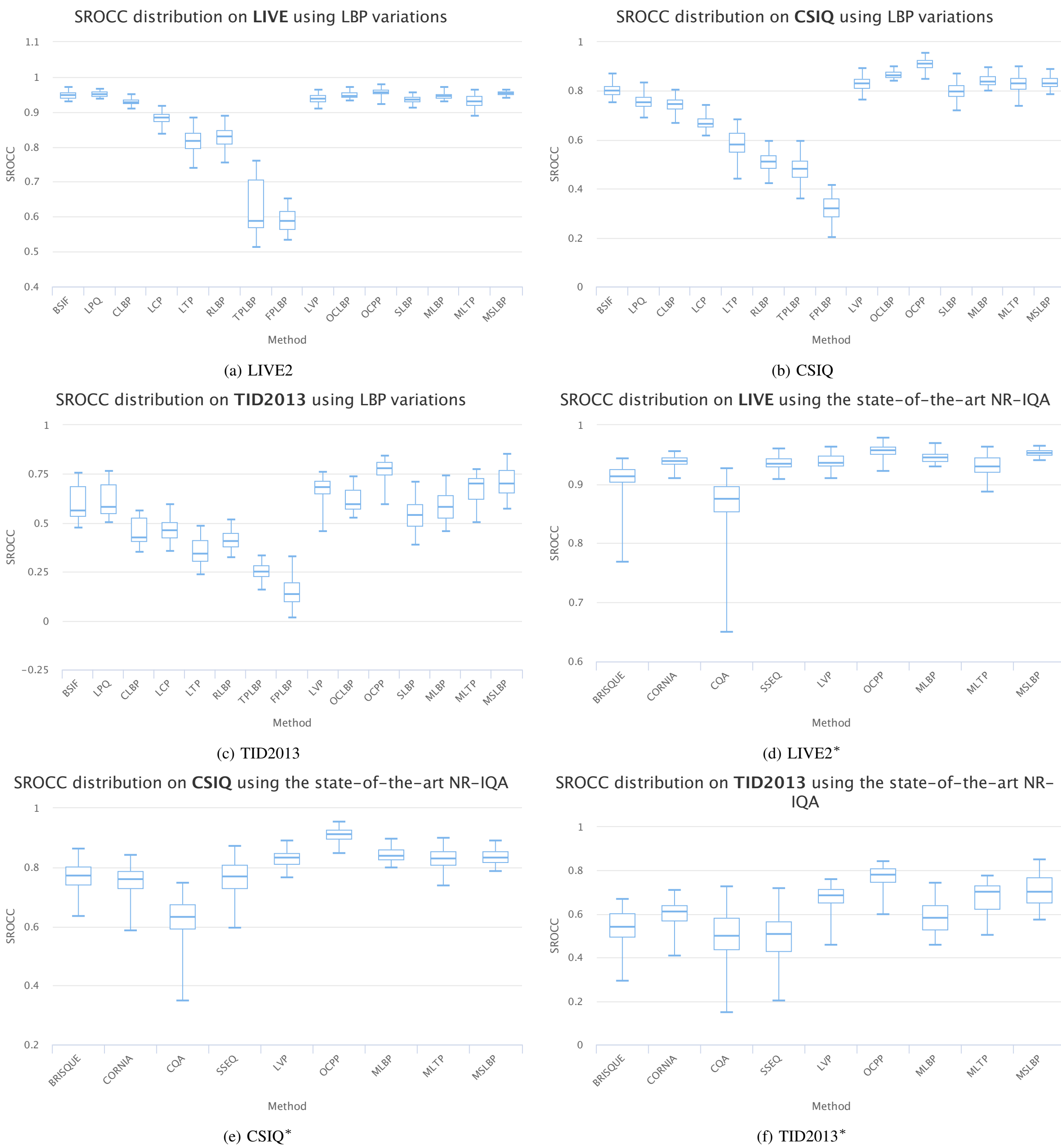
The texture is a fundamental attribute of images. In the context of this work, a texture is the characteristic of an area, which is perceived as the combination of some basic patterns. These basic patterns present a certain regularity that appears in the statistical measures of the visual stimuli. To characterize a texture, a method identifies and selects a set of distinguishing and relevant features. Several methods have been proposed to characterize textures, including gray level co-occurrence matrices (GLCM), texture spectrum, and local binary patterns (LBP). Among the aforementioned methods, the LBP descriptor is one of the most popular methods. Its popularity is due to its ability to describe texture information using a simple descriptor-based approach. Because of its simplicity, this method had a big impact on several computer vision applications, such as face recognition, gender classification, among others. Despite its flexibility, performance, and popularity, the LBP descriptor has many limitations, which have inspired the development of variants that are better adapted to the different applications.

Part of the research conducted in this thesis is to investigate the use of state-of-the-art LBP variants to describe visual quality. Among the studied variants are:

- ▷ Local Ternary Patterns (LTP) [15];
- ▷ Local Phase Quantization (LPQ) [16];
- ▷ Binarized Statistical Image Features (BSIF) [17], [18];
- ▷ Rotated Local Binary Patterns (RLBP) [19], [20];
- ▷ Complete Local Binary Patterns (CLBP) [21];
- ▷ Local Configuration Patterns (LCP) [22];
- ▷ Opposite Color Local Binary Patterns (OCLBP) [23];
- ▷ Three-Patch Local Binary Patterns (TPLBP) [24];
- ▷ Four-Patch Local Binary Patterns (FPLBP) [24].

Experimental results show that the above LBP variants can be used to describe (and estimate) image quality in some contexts. However, we noticed that the robustness of these descriptors can make it difficult to detect some types of degradations and, therefore, to estimate the overall quality. We also observed that multiscale texture descriptors are more suitable for quality estimation. Taking into consideration these observations, we developed six quality-aware texture descriptors in this thesis. The proposed quality-aware descriptors are:

- ▷ Multiscale Local Binary Patterns (MLBP) [25];
- ▷ Multiscale Local Ternary Patterns (MLTP) [26];
- ▷ Local Variance Patterns (LVP) [27];
- ▷ Orthogonal Color Planes Patterns (OCPP) [28];
- ▷ Salient Local Binary Patterns (SLBP) [29];
- ▷ Multiscale Salient Local Binary Patterns (MSLBP) [30].



(a) LIVE2

(b) CSIQ

(c) TID2013

(d) LIVE2*

(e) CSIQ*

(f) TID2013*

Fig. 3. Distribution of average SROCC after 1000 simulations using different texture descriptors (a, b, and c) and comparison with different state-of-the-art methods (d, e, and f).

III. Image Quality Assessment Using Spatial Texture Measures

We proposed a generic quality assessment method that is based on a supervised learning approach. Block diagrams of the training and predicting stages of the proposed method are depicted in Fig. 2(a) and 2(b), respectively. First, we collect subjective scores corresponding to each image of a training set. This procedure generates a set of labeled images, where each training set entry is composed by a pair of an image and its associated MOS (mean observer score). Then, we train the model by extracting features from each image and associating them to the corresponding MOS. After generating the prediction model, the image quality can be predicted using the trained model.

Once it has been demonstrated that basic LBP variants present a suitable descriptor to describe image quality, we check the performance of other LBP extensions mentioned in Section II. To perform the tests, we variate the parameters of BSIF, LPQ, and CLBP descriptors. For the remaining extensions (i.e., LCP, LTP, RLBP, TPLBP, FPLBP, LVP, OCLBP, OCPP, SLBP, MLBP, MLTP, and MSLBP), we do not variate the parameters. Figs. 3(a), (b), and (c) depict the distribution of SROCC over simulations on the general case using the tested LBP variants.

The performed tests indicate that multiscale approaches increase substantially the overall quality prediction performance. Among the multiscale approaches, the MSLBP descriptor, which incorporates visual saliency information for the multiple scales of the LBP maps, presents the best accuracy performance. For the LIVE2 database, the MSLBP and OCPP descriptors have similar performances. However, for the set of all tested databases, the OCPP descriptor has the best overall performance, when compared to the other LBP-based descriptors and to current state-of-the-art quality assessment methods.

Fig.3(d), (e), and (f) indicate that the state-of-the-art methods CORNIA and SSEQ present a performance similar to some LBP-based descriptors, such as CLBP_{SM} and BSIF. However, several LBP-based descriptors present a notable performance, being superior to the state-of-the-art methods, as we can observe from results of LPQ, MLBP, MSLBP, and OCPP with average SROCC above 0.94 on LIVE2. We can also notice that LBP-based NR-IQA approaches present better performance also on CSIQ and TID2013 databases. On CSIQ, we can observe that, on average, the best state-of-the-art NR-IQA method is BRISQUE, followed by SSEQ and CORNIA. The average SROCC scores are 0.7406, 0.6979, and 0.6886 for BRISQUE, SSEQ, and CORNIA, respectively. However, LPQ, BSIF, LVP, OCLBP, OCPP, SLBP, MLBP, MLTP, and MSLBP descriptors present better results on CSIQ when compared with the state-of-the-art methods. Similarly, on TID2013 database, the best state-of-the-art method is CORNIA, which presents an average SROCC of 0.5361. This value is outperformed by several LBP-based descriptors, such as LVP (0.5428), OCLBP (0.5902), OCPP (0.7035), MLBP (0.5284), MLTP (0.5652), MSLBP (0.5919), and LPQ (0.5518).

IV. Video Quality Assessment Using Spatiotemporal Texture Measures

Based on the results obtained with the method described in the last section, we investigated whether texture information can be used to assess the quality of the videos. Since still images and moving images (videos) are perceived differently by the human vision system (HVS), we added more feature sets to the framework than what was previously used for predicting the quality of still images. The feature sets are composed of:

- multiscale salient local binary patterns (MSLBP) [30],
- multiscale structural similarity (MSSIM) [31],
- gradient magnitude similarity deviation (GMSD) [32],
- Riesz pyramid similarity deviation (RPSD) [33],
- spatial activity (SA) and temporal distortion measures (TDM) [34].

As illustrated in Fig. 4, each of these feature sets is computed for both the reference and assessed videos. For each feature component, a pooling strategy is adopted and the pooled values are concatenated to generate a single feature vector. Finally, the feature vector is used as input to a random forest regressor (RFR) to predict the quality score.

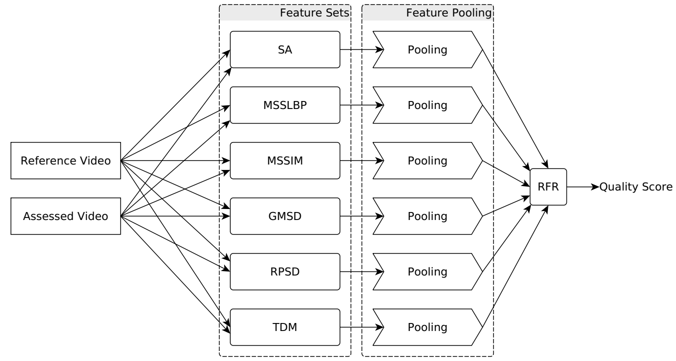


Fig. 4. Block diagram of the proposed video quality assessment method.

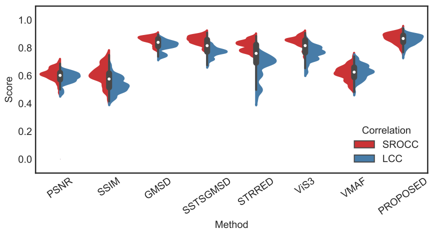
The proposed video quality method is compared with other 7 methods, including 3 image quality metrics plus 4 state-of-the-art video metrics. These results are shown in Fig. 5, which depicts the distribution of the correlation scores over 1,000 rounds of simulations. Fig. 5(a) presents the SROCC and LCC violin plots for the CSIQ dataset. Notice that the proposed method shows the highest SROCC average values, when compared to state-of-the-art metrics, followed by SSTSGMSD, GMSD, ViS3, and STRRED. Since CSIQ contains two transmission-based distortions, it is expected that IQA methods present a worse performance, which explains the differences between the PSNR and SSIM results when compared with other methods. Surprisingly, GMSD presents a competitive performance, having a performance similar to its video-based version, SSTSGMSD.

V. Conclusions

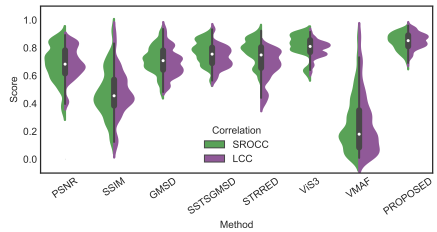
In this thesis, our goal was to investigate how to estimate digital image and video quality for real-time applications, with both blind and full-reference objective metrics that use machine learning approaches. In the proposed approach, visual quality methods were generated using texture measurements. We presented two methods: a no-reference (blind) image quality metric and a full-reference video quality method. In this work, we first presented a general framework to predict image quality using texture descriptors, using the Local Binary Pattern (LBP) and some of its variants. Then, we adapted the texture feature descriptors for video quality assessment.

In short, the thesis at hand contributes to the fields of Multimedia and Computer Vision with the following novelties:

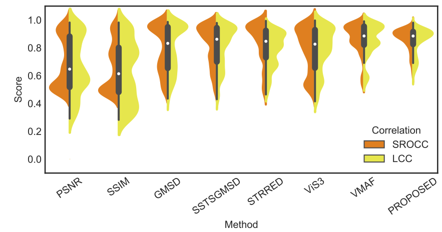
- Development of a set of extensions of the LBP descriptor, which are designed to produce quality-aware features that are useful to predict visual quality.
- Development of a machine learning framework to blindly estimate image quality using texture descriptors.
- Development of a full-reference video quality assessment method using the framework described for still image but with some additional spatio-temporal features.



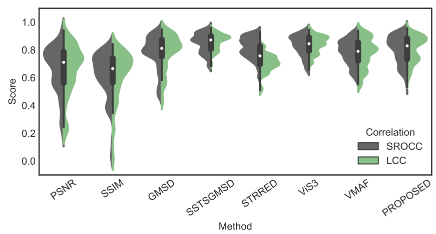
(a) CSIQ



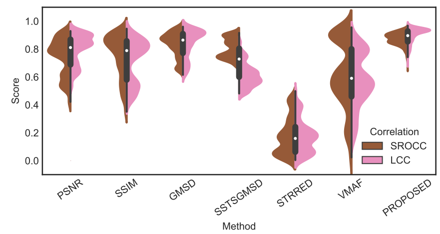
(b) IVPL



(c) MCL-V



(d) LIVE



(e) LIVE-M

Fig. 5. Violin plots of SROCC results of the tested OVQA methods for CSIQ, IVPL, MCL-V, LIVE, and LIVE-M databases.

The proposed solutions are generic enough to be used in multimedia applications that require a quality estimate for images or videos, such as video coding, lossy compression, image restoration, etc. Moreover, the proposed methods can be extended for another type of visual data, such as point clouds, 3D videos, and light fields. As future work, another type of descriptors that produce texture features that are sensitive to other types of distortions (such as color, contrast, etc.) can be designed.

VI. Research Accomplishments

As a result of the work produced in this Ph.D. dissertation, **23 papers** were produced and **2 awards** were received :

◇ Published Conference Papers:

C1: *"A Parallel Framework for Video Super-Resolution"* – SIBGRAPI, 2014

C2: *"Tampering Detection of Audio-Visual Content Using Encrypted Watermarks"* – SIBGRAPI, 2014.

C3: *"Embedding Color Watermarks Into Halftoning Images Using Minimum-Distance Binary Patterns"* – SIBGRAPI, 2015.

C4: *"Improved Performance of Inverse Halftoning Algorithms via Coupled Dictionaries"* – ICME, 2015.

C5: *"Video Quality Ruler: A New Experimental Methodology for Assessing Video Quality"* – QoMEX, 2015.

C6: *"No-Reference Image Quality Assessment Using Texture Information Banks"* – BRACIS, 2016.

C7: *"No-reference Image Quality Assessment Based on Statistics of Local Ternary Pattern"* – QoMEX, 2016.

C8: *"Blind Image Quality Assessment Using Local Variant Patterns"* - BRACIS, 2017.

C9: *"On the Performance of Visual Semantics for Improving Texture-based Blind Image Quality Assessment"* – SIBGRAPI, 2017.

C10: *"No-reference Image Quality Assessment Using Salient Local Binary Patterns"* – Electronic Imaging, 2018.

C11: *"Blind Image Quality Assessment Based on Multiscale Salient Local Binary Patterns"* – ACM Multimedia Systems, 2018.

◇ Accepted Conference Papers:

C12: *"Towards a Referenceless Visual Quality Assessment Model Using Binarized Statistical Image Features"* – BRACIS, 2018. ***Accepted***.

◇ Published Journal Papers:

J1: *"A Parallel Framework for Video Super-resolution"* – Electronic Letters on Computer Vision and Image Analysis (ELCVIA), 2014 – **Qualis B2**.

J2: *"Detecting Tampering in Audio-Visual Content Using QIM Watermarking"* – Information Sciences, 2016 – **Qualis A1**

J3: *"Enhancing Inverse Halftoning via Coupled Dictionary Training"* – Signal Processing: Image Communication, 2016 – **Qualis A2**.

J4: *"Secure Self-Recovery Watermarking Scheme for Error Concealment and Tampering Detection"* – Journal of The Brazilian Computer Society, 2016 – **Qualis B1**.

J5: *"Hiding Color Watermarks in Halftone Images Using Maximum-Similarity Binary Patterns"* – Signal Processing: Image Communication, 2016 – **Qualis A2**.

J6: *"Blind Image Quality Assessment Using Multiscale Local Binary Patterns"* – Journal of Imaging Science and Technology, 2017 – **Qualis B4**.

J7: *"Using Multiple Spatio-temporal Features to Estimate Video Quality"* – Signal Processing: Image Communication, 2018 – **Qualis A2**.

J8: *"No-Reference Image Quality Assessment Using Orthogonal Color Planes Patterns"* – Transactions on Multimedia, 2018 – **Qualis A1**.

◇ Submitted Journal Papers:

J9: *"Performance Analysis of a Video Quality Ruler Methodology for Subjective Quality Assessment"* – Transactions on Broadcasting, 2018 – **Qualis A2**. ***Under review.***

J10: *"Image Quality Assessment by Saliency, Color-Texture Energy and Gradient Boosting Machines"* – Journal of the Brazilian Computer Society, 2018 – **Qualis B1**. ***Accepted.***

J11: *"A Framework for Computationally Efficient Video Quality Assessment"* – Signal Processing: Image Communication, 2018 – **Qualis A2**. ***Under review.***

◇ Awards:

A1: **Honorable mention award** in the main track for the work *"Embedding Color Watermarks into Halftoning Images using Minimum-Distance Binary Patterns"* presented in the 28th Conference on Graphics, Patterns and Images (SIBGRAPI), Salvador, Brazil, on August 26–29, 2015.

A2: **Best student paper award** in the Image Quality and System Performance track for the work *"Blind Image Quality Assessment Using Multiscale Local Binary Patterns"* presented in the International Symposium on Electroning Imaging, Burlingame, California, on February 29, 2017.

The publications derived from this Ph.D. dissertation are available at: https://www.dropbox.com/s/f8t4iqutdqf8hc3/

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