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16th December 2021

QAH working group
Quality Assessment for Health Applications

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What we did in 2021

1) **Topical review** published in July:

Physics in Medicine & Biology

TOPICAL REVIEW

Comparative study of the methodologies used for subjective medical image quality assessment

Lucie Lévêque[1], Meriem Outtas[2], Hantao Liu[3] and Lu Zhang[2]

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Physics in Medicine & Biology, Volume 66, Number 15

Citation Lucie Lévêque *et al* 2021 *Phys. Med. Biol.* **66** 15TR02

- State-of-the-art of recent works on subjective QA + task-based approaches
- Discussion on merits and drawbacks of the methodologies + recommendations
- List + lack of available annotated medical databases

What we did in 2021

2) **Special session** submitted to *ICIP 2022*:

Quality Assessment for Medical Imaging Applications

Topics of interest

We are seeking papers that include, but are not limited to, the following topics:

- Subjective and objective experiments for medical image quality assessment.
- Relationship between perceptual and task-based medical image quality.
- Task-based assessment based on model observers (including synthesised images).
- Computer-based medical image perception.
- Datasets with new diagnostic tasks.
- Medical objective image quality assessment models.
- Methodologies, and guidelines for subjective medical image quality assessment.
- Perceptual (quality-guided) medical image processing (enhancement, segmentation, coding, and watermarking).

3) **Topical review** submitted to *Medical Image Analysis*, to be presented now!

Objective Quality Assessment of Medical Images and Videos:

Review and Challenges

Rafael Rodrigues[1], Lucie Lévêque[2], Jesús Gutiérrez[3], Houda Jebbari[4], Meriem Outtas[4], Lu Zhang[4], Aladine Chetouani[5], Shaymaa Al-Juboori[6], Maria G. Martini[6], and Antonio M.G. Pinheiro[1]

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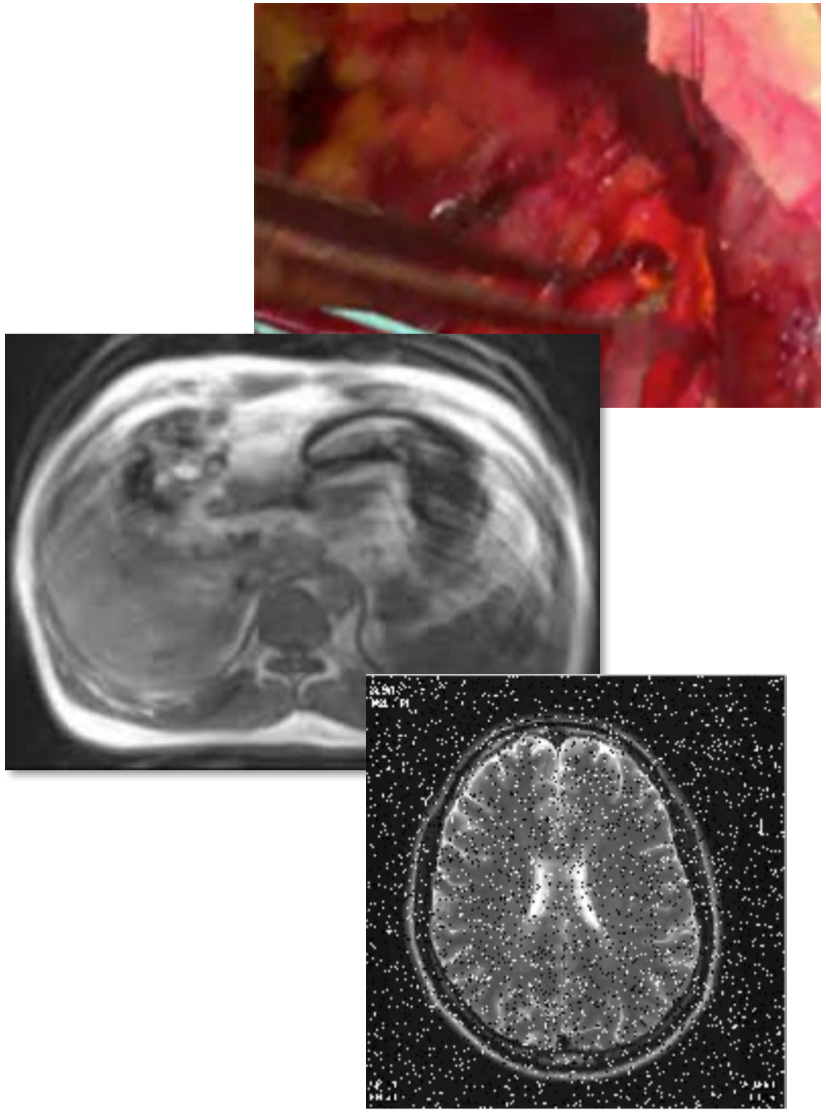
INTRODUCTION

- Impairments in medical image and video depend on **acquisition and reconstruction-related factors**, specific to each imaging modality (e.g., radiation dose for CT scans, or magnetic field homogeneity for MRI).

- Images and videos may also be subject to different **processing, compression/encoding, transmission, and visualisation** methods.

- Image and video QA in health applications is a necessity, towards improving methodologies throughout the clinical workflow; but also a very challenging field, given the **diversity of content, impairments, and applications**.



OVERVIEW

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SUBJECTIVE
QUALITY
ASSESSMENT

Lévêque *et al.*,
Physics in Medicine & Biology, 2021.

OBJECTIVE
QUALITY
ASSESSMENT

- Visual quality-based approaches

  Compute quality index directly from **visual and/or structural information** of the images and videos

- Task-based approaches

  Designed to approximate the **performance of human observers on a given task**

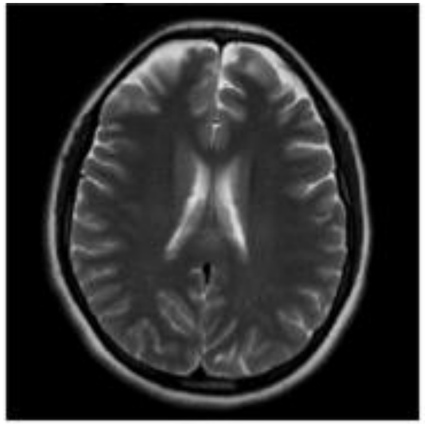
VISUAL QUALITY-BASED METHODS

- **Visual quality-based methods**
  - Full-reference metrics (FR)
  - Reduced-reference metrics (RR)
  - No-reference metrics (NR)

VISUAL QUALITY-BASED METHODS

References by imaging modality:

- Magnetic Resonance Imaging (MRI) – 11
- Retinal fundus photography – 7
- Ultrasonography – 7
- Computed Tomography (CT) – 5
- Endoscopic/laparoscopic video – 5
- Fused images (MRI, CT, PET, SPECT, US) – 2
- X-ray (planar) – 1
- Ocular Coherence Tomography – 1



Mason et al. 2019

Alais et al. 2020

TASK-BASED METHODS

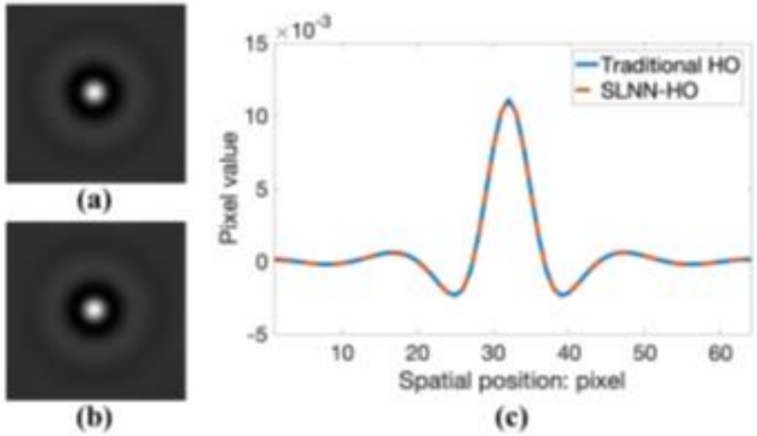
Task-based methods

- **Detection and classification**
- Estimation
- **Localisation**
- **Segmentation**
- Characterisation

TASK-BASED METHODS

References by imaging modality:

- Computed Tomography (CT) – 4 (phantom studies)
- Computer-simulated images – 4
- Retinal fundus photography – 2
- Magnetic Resonance Imaging (MRI) – 1
- Mammography - 1
- Ultrasound – 1



Zhou et al. 2019

Wu et al. 2017

DISCUSSION AND FUTURE WORK

- Regarding FR and RR visual quality-based metrics, all the reviewed papers reported the use of **metrics originally developed for natural content.**

- **FR metrics: PSNR and SSIM** were the most commonly used metrics (10 studies). VIF and NQM were also used frequently.

- Only one paper reported a FR metric specifically designed for medical content (Razaak and Martini, 2016).
  M. Razaak and M. G. Martini, "CUQI: cardiac ultrasound video quality index," *Journal of Medical Imaging*, vol. 3, no. 1, p. 011011, 2016.

- As for NR metrics, most papers proposed metrics tailored for the considered content.

- **Deep learning methods are becoming a staple in NR quality assessment of medical image and video:** most recent studies used CNN instead of handcrafted features.

DISCUSSION AND FUTURE WORK

- **Lack of subjective annotated quality databases** (Lévêque *et al.* (2021)): only 3 databases, by Suad *et al.* (2013), Outtas *et al.* (2018), and Khan *et al.* (2020).

- Regarding task-based QA, annotated datasets should **incorporate models of how clinicians perform diagnosis from images and videos**, for example.

- In order to address these issues, Willemink *et al.* (2020) suggested using human-in-the-loop machine learning.
AI techniques promise a strong breakthrough in medical imaging objective QA.

- L. Lévêque, M. Outtas, H. Liu, and L. Zhang, "Comparative study of the methodologies used for subjective medical image quality assessment," *Physics in Medicine & Biology*, vol. 66, no. 15, 2021.
- J. Suad and W. Jbara, "Subjective quality assessment of new medical image database," *International Journal of Computer Engineering and Technology*, vol. 4, pp. 155–164, 2013.
- M. Outtas, L. Zhang, O. Deforges, A. Serir, and W. Hamidouche, "Subjective and objective evaluations of feature selected multi output filter for speckle reduction on ultrasound images," *Physics in Medicine & Biology*, vol. 63, no. 18, 2018.
- Z. A. Khan, A. Beghdadi, F. A. Cheikh, M. Kaaniche, E. Pelanis, R. Palomar, ˚A. A. Fretland, B. Edwin, and O. J. Elle, "Towards a video quality assessment based framework for enhancement of laparoscopic videos," in *Medical Imaging 2020: Image Perception, Observer Performance, and Technology Assessment*, vol. 11316. International Society for Optics and Photonics, 2020, p. 113160P.
- M. Willemink, W. Koszek, C. Hardell, J. Wu, D. Fleischmann, H. Harvey, L. Folio, R. Summers, D. Rubin, and M. Lungren, "Preparing medical imaging data for machine learning," *Radiology*, vol. 295, no. 1, 2020.

DISCUSSION AND FUTURE WORK

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- Another challenge for objective medical QA is **artifact simulation**. Collecting data with real artifacts may be impractical or not always possible.
- However, **simulated artifacts are normally limited in their range**, which may hinder the application of developed QA methods to real clinical data (Oh *et al.*, 2021).
- Some efforts are reported, concerning the simulation of content-specific and realistic artifacts (Yang *et al.*, 2019; Oktaviana *et al.*, 2019; Hu *et al.*, 2021; Oh *et al.*, 2021).
- Deep learning methods, e.g., Generative Adversarial Networks (GANs) may provide interesting solutions.

- G. Oh, J. E. Lee, and J. C. Ye, "Unpaired MR motion artifact deep learning using outlier-rejecting bootstrap aggregation," *IEEE Transactions on Medical Imaging*, vol. 40, no. 11, pp. 3125–3139, 2021.
- J. Yang, M. Faraji, and A. Basu, "Robust segmentation of arterial walls in intravascular ultrasound images using dual path U-Net," *Ultrasonics*, vol. 96, pp. 24–33, 2019.
- A. Oktaviana, S. Pawiro, T. Siswatining, and D. Soejoko, "Preliminary study of ring artifact detection in SPECT imaging using Jaszczak phantom," in *Journal of Physics: Conference Series*, vol. 1248, no. 1. IOP Publishing, 2019, p. 012030.
- R. Hu, R. Yang, Y. Liu, and X. Li, "Simulation and mitigation of the wrap-around artifact in the MRI image," *Frontiers in Computational Neuroscience*, vol.15, p. 89, 2021.

DISCUSSION AND FUTURE WORK

- In task-based QA, traditional model observers are based on statistical characteristics of the images. Hence, **many studies rely on phantom or simulated images**.
- Currently, **there is no evidence that studies conducted on simulated images** ensure sufficient confidence to draw relevant conclusions on real clinical data.
- **DL methods could address these limitations**, as task performance provides a direct quality measure. The challenge is to define which tasks may be reliably delegated.
- To our knowledge, **existing models are limited in terms of task range**. Characterisation tasks are highly complex and involve a linguistic response (e.g., benign *vs.* malign). Other tasks include estimation tasks, which aim at determining a scalar or range of values for an object parameter (e.g., tumour diameter).

DISCUSSION AND FUTURE WORK

- 3D visualisation of medical content (e.g., using stereoscopic or light field) opens new opportunities, e.g., surgery training (Martini *et al.*, 2013). But QA research is still behind.

- Compression and transmission of 3D stereoscopic, as well of light field, medical content, **require suitable metrics for the assessment of their performance**.
  Studies on QA for light field medical images have started (Kara *et al.*, 2017).

- Future research might focus on **evaluating the performance of existing metrics for generic 3D images and videos** (e.g., Han *et al.*, 2016; Battisti *et al.*, 2015) **and light field data** (e.g., Ak and Le Callet, 2019; Tamboli *et al.*, 2018) on medical data.
  The availability of medical datasets in stereoscopic and light field formats is in demand.

- M. G. Martini, C. T. Hewage, M. M. Nasralla, R. Smith, I. Jourdan, and T. Rockall, “3D robotic tele-surgery and training over next generation wireless networks,” in *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2013, pp. 6244–6247.
- P. A. Kara, P. T. Kovacs, S. Vagharshakyan, M. G. Martini, S. Imre, A. Barsi, K. Lackner, and T. Balogh, “Perceptual quality of reconstructed medical images on projection-based light field displays,” in *eHealth 360°*. Springer, 2017, pp. 476–483.
- Y. Han, Z. Yuan, and G.-M. Muntean, “An innovative no-reference metric for real-time 3D stereoscopic video quality assessment,” *IEEE Transactions on Broadcasting*, vol. 62, no. 3, pp. 654–663, 2016.
- F. Battisti, E. Bosc, M. Carli, P. Le Callet, and S. Perugia, “Objective image quality assessment of 3D synthesized views,” *Signal Processing: Image Communication*, vol. 30, pp. 78–88, 2015.
- A. Ak and P. Le Callet, “Investigating epipolar plane image representations for objective quality evaluation of light field images,” in *European Workshop on Visual Information Processing*, Oct. 2019, pp. 135–139.
- R. R. Tamboli, P. A. Kara, A. Cserkaszky, A. Barsi, M. G. Martini, B. Appina, S. S. Channappayya, and S. Jana, “3D objective quality assessment of light field video frames,” in *3DTV-Conference: The True Vision-Capture, Transmission and Display of 3D Video*, Jun. 2018.

REFERENCES

Visual quality-based metrics

- Full-reference metrics:

- Y. Zhou, D. Chen, C.-f. Li, X.-o. Li, and H.-q. Feng, “A practice of medical image quality evaluation,” in *International Conference on Neural Networks and Signal Processing*, vol. 1, 2003, pp. 204–207.

- I. A. Kowalik-Urbaniak, J. Castelli, N. Hemmati, D. Koff, N. Smolarski-Koff, E. R. Vrscay, J. Wang, and Z. Wang, “Modelling of subjective radiological assessments with objective image quality measures of brain and body CT images,” in *International Conference Image Analysis and Recognition*. Springer, 2015, pp. 3–13.

- A. Panayides, M. S. Pattichis, C. S. Pattichis, C. P. Loizou, M. Pantziaris, and A. Pitsillides, “Atherosclerotic plaque ultrasound video encoding, wireless transmission, and quality assessment using H.264,” *IEEE Transactions on Information Technology in Biomedicine*, vol. 15, no. 3, pp. 387–397, 2011.

- M. Razaak, M. G. Martini, and K. Savino, “A study on quality assessment for medical ultrasound video compressed via HEVC,” *IEEE Journal of Biomedical and Health Informatics*, vol. 18, no. 5, pp. 1552–1559, 2014.

- M. Razaak and M. G. Martini, “CUQI: cardiac ultrasound video quality index,” *Journal of Medical Imaging*, vol. 3, no. 1, p. 011011, 2016.

- A. E. Kumcu, K. Bombeke, H. Chen, L. Jovanov, L. Platisa, H. Q. Luong, J. Van Looy, Y. Van Nieuwenhove, P. Schelkens, and W. Philips, “Visual quality assessment of H.264/AVC compressed laparoscopic video,” in *Medical Imaging 2014: Image Perception, Observer Performance, and Technology Assessment*, vol. 9037. International Society for Optics and Photonics, 2014, p. 90370A.

- M. A. Usman, M. R. Usman, and S. Y. Shin, “Quality assessment for wireless capsule endoscopy videos compressed via HEVC: from diagnostic quality to visual perception,” *Computers in Biology and Medicine*, vol. 91, pp. 112–134, 2017.

REFERENCES

Visual quality-based metrics

- Full-reference metrics:

- B. Kumar, S. P. Singh, A. Mohan, and H. V. Singh, “MOS prediction of SPIHT medical images using objective quality parameters,” in International Conference on Signal Processing Systems, 2009, pp. 219–223.

- B. Kumar, S. B. Kumar, and C. Kumar, “Development of improved SSIM quality index for compressed medical images,” in *IEEE International Conference on Image Information Processing*, 2013, pp. 251–255.

- G. P. Renieblas, A. T. Nogués, A. M. González, N. G. León, and E. G. Del Castillo, “Structural similarity index family for image quality assessment in radiological images,” *Journal of Medical Imaging*, vol. 4, no. 3, p. 035501, 2017.

- A. Chaabouni, Y. Gaudeau, J. Lambert, J.-M. Moureaux, and P. Gallet, “H.264 medical video compression for telemedicine: a performance analysis,” *Innovation and Research in Biomedical Engineering*, vol. 37, no. 1, pp. 40–48, 2016.

- A. Mason, J. Rioux, S. E. Clarke, A. Costa, M. Schmidt, V. Keough, T. Huynh, and S. Beyea, “Comparison of objective image quality metrics to expert radiologists’ scoring of diagnostic quality of MR images,” *IEEE Trans. on Medical Imaging*, vol. 39, no. 4, pp. 1064–1072, 2019.

- L. S. Chow, H. Rajagopal, R. Paramesran, Alzheimer’s Disease Neuroimaging Initiative et al., “Correlation between subjective and objective assessment of magnetic resonance (MR) images,” *Magnetic Resonance Imaging*, vol. 34, no. 6, pp. 820–831, 2016.

REFERENCES

Visual quality-based metrics

- Reduced-reference metrics:

- S. C. Lee and Y. Wang, "Automatic retinal image quality assessment and enhancement," in *Medical Imaging 1999: image Processing*, vol. 3661. International Society for Optics and Photonics, 1999, pp. 1581–1590.

- M. Lalonde, L. Gagnon, M.-C. Boucher *et al.*, "Automatic visual quality assessment in optical fundus images," in *Proceedings of Vision Interface*, vol. 32. Ottawa, 2001, pp. 259–264.

- B. M. Planitz and A. J. Maeder, "A study of block-based medical image watermarking using a perceptual similarity metric," in *Digital Image Computing: Techniques and Applications*, Dec. 2005.

- K. M. Nasr and M. G. Martini, "A visual quality evaluation method for telemedicine applications," *Signal Processing: Image Communication*, vol. 57, pp. 211–218, 2017.

REFERENCES

Visual quality-based metrics

- No-reference metrics:

- A. Liebgott, T. Küstner, S. Gatidis, F. Schick, and B. Yang, "Active learning for magnetic resonance image quality assessment," in *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2016, pp. 922–926.

- L. S. Chow and H. Rajagopal, "Modified-BRISQUE as no reference image quality assessment for structural MR images," *Magnetic Resonance Imaging*, vol. 43, pp. 74–87, 2017.

- M. Osadebey, M. Pedersen, D. Arnold, K. Wendel-Mitoraj *et al.*, "Bayesian framework inspired no-reference region-of-interest quality measure for brain MRI images," *Journal of Medical Imaging*, vol. 4, no. 2, p. 025504, 2017.

- S. J. Esses, X. Lu, T. Zhao, K. Shanbhogue, B. Dane, M. Bruno, and H. Chandarana, "Automated image quality evaluation of T2-weighted liver MRI utilizing deep learning architecture," *Journal of Magnetic Resonance Imaging*, vol. 47, no. 3, pp. 723–728, 2018.

- R. Obuchowicz, M. Oszust, M. Bielecka, A. Bielecki, and A. Piórkowski, "Magnetic resonance image quality assessment by using non-maximum suppression and entropy analysis," *Entropy*, vol. 22, no. 2, p. 220, 2020.

- J. J. Ma, U. Nakarmi, C. Y. S. Kin, C. M. Sandino, J. Y. Cheng, A. B. Syed, P. Wei, J. M. Pauly, and S. S. Vasanawala, "Diagnostic image quality assessment and classification in medical imaging: opportunities and challenges," in *2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI)*. IEEE, 2020, pp. 337–340.

- S. Chabert, J. S. Castro, L. Muñoz, P. Cox, R. Riveros, J. Vielma, G. Huerta, M. Querales, C. Saavedra, A. Veloz *et al.*, "Image quality assessment to emulate experts' perception in lumbar MRI using machine learning," *Applied Sciences*, vol. 11, no. 14, p. 6616, 2021.

REFERENCES

Visual quality-based metrics

- No-reference metrics:

- T. Köhler, A. Budai, M. F. Kraus, J. Odstrcilik, G. Michelson, and J. Hornegger, “Automatic no-reference quality assessment for retinal fundus images using vessel segmentation,” in Proceedings of the *26th IEEE International Symposium on Computer-based Medical Systems*. IEEE, 2013, pp. 95–100.

- S. Wang, K. Jin, H. Lu, C. Cheng, J. Ye, and D. Qian, “Human visual system-based fundus image quality assessment of portable fundus camera photographs,” *IEEE Transactions on Medical Imaging*, vol. 35, no. 4, pp. 1046–1055, 2015.

- A. S. Coyner, R. Swan, J. P. Campbell, S. Ostmo, J. M. Brown, J. Kalpathy-Cramer, S. J. Kim, K. E. Jonas, R. P. Chan, M. F. Chiang *et al.*, “Automated fundus image quality assessment in retinopathy of prematurity using deep convolutional neural networks,” *Ophthalmology Retina*, vol. 3, no. 5, pp. 444–450, 2019.

- A. Raj, N. A. Shah, A. K. Tiwari, and M. G. Martini, “Multivariate regression-based convolutional neural network model for fundus image quality assessment,” *IEEE Access*, vol. 8, pp. 57 810–57 821, 2020.

- Y. Shen, B. Sheng, R. Fang, H. Li, L. Dai, S. Stolte, J. Qin, W. Jia, and D. Shen, “Domain-invariant interpretable fundus image quality assessment,” *Medical Image Analysis*, vol. 61, p. 101654, 2020.

- S. I. Niwas, V. Jakhetiya, W. Lin, C. K. Kwoh, C. C. Sng, M. C. Aquino, K. Victor, and P. T. Chew, “Complex wavelet based quality assessment for AS-OCT images with application to Angle Closure Glaucoma diagnosis,” *Computer Methods and Programs in Biomedicine*, vol. 130, pp. 13–21, 2016

- Z. A. Khan, A. Beghdadi, M. Kaaniche, and F. A. Cheikh, “Residual networks based distortion classification and ranking for laparoscopic image quality assessment,” in *2020 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2020, pp. 176–180.

REFERENCES

Visual quality-based metrics

- No-reference metrics:

- S. Ali, F. Zhou, A. Bailey, B. Braden, J. E. East, X. Lu, and J. Rittscher, "A deep learning framework for quality assessment and restoration in video endoscopy," *Medical Image Analysis*, vol. 68, p. 101900, 2021.

- A. H. Abdi, C. Luong, T. Tsang, G. Allan, S. Nouranian, J. Jue, D. Hawley, S. Fleming, K. Gin, J. Swift *et al.*, "Automatic quality assessment of echocardiograms using convolutional neural networks: feasibility on the apical four-chamber view," *IEEE Transactions on Medical Imaging*, vol. 36, no. 6, pp. 1221–1230, 2017.

- L. Tang, C. Tian, J. Qian, and L. Li, "No reference quality evaluation of medical image fusion," *International Journal of Imaging Systems and Technology*, vol. 28, no. 4, pp. 267–273, 2018.

- L. Tang, C. Tian, L. Li, B. Hu, W. Yu, and K. Xu, "Perceptual quality assessment for multimodal medical image fusion," *Signal Processing: Image Communication*, vol. 85, p. 115852, 2020.

- M. Outtas, L. Zhang, O. Deforges, W. Hammidouche, A. Serir, and C. Cavaro-Menard, "A study on the usability of opinion-unaware no-reference natural image quality metrics in the context of medical images," in *2016 International Symposium on Signal, Image, Video and Communications (ISIVC)*, Nov 2016, pp. 308–313.

REFERENCES

Task-based metrics

- Detection/Classification:

- B. L. Eck, R. Fahmi, K. M. Brown, S. Zabic, N. Raihani, J. Miao, and D. L. Wilson, "Computational and human observer image quality evaluation of low dose, knowledge-based CT iterative reconstruction," *Medical Physics*, vol. 42, no. 10, pp. 6098–6111, 2015.

- D. Racine, A. H. Ba, J. G. Ott, F. O. Bochud, and F. R. Verdun, "Objective assessment of low contrast detectability in computed tomography with Channelized Hotelling Observer," *Physica Medica*, vol. 32, no. 1, pp. 76–83, 2016.

- J. Greffier, J. Frandon, A. Larbi, J. Beregi, and F. Pereira, "CT iterative reconstruction algorithms: a task-based image quality assessment," *European Radiology*, vol. 30, no. 1, pp. 487–500, 2020.

- F. K. Kopp, M. Catalano, D. Pfeiffer, A. A. Fingerle, E. J. Rummeny, and P. B. No¨el, "CNN as model observer in a liver lesion detection task for X-ray computed tomography: a phantom study," *Medical Physics*, vol. 45, no. 10, pp. 4439–4447, 2018.

- W. Zhou, H. Li, and M. A. Anastasio, "Approximating the Ideal Observer and Hotelling Observer for binary signal detection tasks by use of supervised learning methods," *IEEE Transactions on Medical Imaging*, vol. 38, no. 10, pp. 2456–2468, 2019.

- M. Alnowami, G. Mills, M. Awis, P. Elangovanr, M. Patel, M. Halling-Brown, K. Young, D. R. Dance, and K. Wells, "A deep learning model observer for use in alterative forced choice virtual clinical trials," in *Medical Imaging 2018: Image Perception, Observer Performance, and Technology Assessment*, vol. 10577. International Society for Optics and Photonics, 2018, p. 105770Q.

- K. Li, W. Zhou, H. Li, and M. A. Anastasio, "Assessing the impact of deep neural network-based image denoising on binary signal detection tasks," IEEE Transactions on Medical Imaging, vol. 40, no. 9, pp. 2295– 2305, 2021

REFERENCES

Task-based metrics

- Localisation:

- L. Wu, J.-Z. Cheng, S. Li, B. Lei, T. Wang, and D. Ni, "FUIQA: Fetal ultrasound image quality assessment with deep convolutional networks," *IEEE Transactions on Cybernetics*, vol. 47, no. 5, pp. 1336–1349, 2017.

- W. Zhou, H. Li, and M. A. Anastasio, "Approximating the Ideal Observer for joint signal detection and localization tasks by use of supervised learning methods," *IEEE Transactions on Medical Imaging*, vol. 39, no. 12, pp. 3992–4000, 2020.

-I. Lorente, C. K. Abbey, and J. G. Brankov, "Deep learning based model observer by U-Net," in *Medical Imaging 2020: Image Perception, Observer Performance, and Technology Assessment*, vol. 11316. International Society for Optics and Photonics, 2020, p. 113160F.

- Segmentation:

- R. Welikala, M. Fraz, P. Foster, P. Whincup, A. R. Rudnicka, C. G. Owen, D. Strachan, S. A. Barman et al., "Automated retinal image quality assessment on the UK Biobank dataset for epidemiological studies," Computers in biology and medicine, vol. 71, pp. 67–76, 2016.

- R. Rodrigues and A. M. G. Pinheiro, "A quality of recognition case study: texture-based segmentation and MRI quality assessment," in *2019 27th European Signal Processing Conference (EUSIPCO)*, Nov. 2019.

- R. Alais, P. Dokladal, A. Erginay, B. Figliuzzi, and E. Decencière, "Fast macula detection and application to retinal image quality assessment," *Biomedical Signal Processing and Control*, vol. 55, p. 101567, 2020. **(Localisation and segmentation)**

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