Analysing and quantifying visual experience in medical imaging

A thesis submitted in partial fulfilment of the requirement for the degree of

Doctor of Philosophy

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Abstract

Healthcare professionals increasingly view medical images and videos in a variety of environments. The perception and interpretation of medical visual information across all specialties, career stages, and practice settings are critical to patient care and safety. However, medical images and videos are not self-explanatory and thus need to be interpreted by humans, who are prone to errors caused by the inherent limitations of the human visual system. It is essential to understand how medical experts perceive visual content, and use this knowledge to develop new solutions to improve clinical practice. Progress has been made in the literature towards such understanding, however studies remain limited.

This thesis investigates two aspects of human visual experience in medical imaging, i.e., visual quality assessment and visual attention. Visual quality assessment is important as diverse visual signal distortion may arise in medical imaging and affect the perceptual quality of visual content, and therefore potentially impact the diagnosis accuracy. We adapted existing qualitative and quantitative methods to evaluate the quality of distorted medical videos. We also analysed the impact of medical specialty on visual perception and found significant differences between specialty groups, e.g., sonographers were in general more bothered by visual distortions than radiologists. Visual attention has been studied in medical imaging using eye-tracking technology. In this thesis, we firstly investigated gaze allocation with radiologists analysing two-view mammograms and secondly assessed the impact of expertise and experience on gaze behaviour. We also evaluated to what extent state-of-the-art visual attention models can predict radiologists' gaze behaviour and showed the limitations of existing models.

This thesis provides new experimental designs and statistical processes to evaluate the perception of medical images and videos, which can be used to optimise the visual experience of image readers in clinical practice.

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Je dédicace cette thèse à mon Papy, le meilleur. Tu nous manques énormément.

Lucie

PS: “The future belongs to those who believe in the beauty of their dreams.”
– Eleanor Roosevelt

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List of publications

The work presented in this thesis is based on the following peer-reviewed publications. More specifically,

Chapter 2 is based on:

L. Lévêque et al., “On the Subjective Assessment of the Perceptual Quality of Medical Images and Videos”, *10th International Conference on Quality of Multimedia Experience (QoMEX), Sardinia, Italy*, May 2018.

L. Lévêque, H. Bosmans, L. Cockmartin, and H. Liu, “State of the Art: Eye-Tracking Studies in Medical Imaging”, *IEEE Access*, vol. 6, pp. 37023-37034, June 2018.

Chapter 3 is based on:

L. Lévêque, W. Zhang, C. Cavaro-Ménard, P. Le Callet, and H. Liu, "Study of Video Quality Assessment for Telesurgery”, *IEEE Access*, vol. 5, pp. 9990-9999, May 2017.

L. Lévêque, H. Liu, C. Cavaro-Ménard, Y. Cheng, and P. Le Callet, "Video Quality Perception in Telesurgery", *19th IEEE International Workshop on Multimedia Signal Processing (MMSP), Luton, United Kingdom*, October 2017.

Chapter 4 is based on:

L. Lévêque, W. Zhang, P. Parker, and H. Liu, “The Impact of Specialty Settings on the Perceived Quality of Medical Ultrasound Video”, *IEEE Access*, vol. 5, pp. 16998-17005, August 2017.

Chapter 6 is based on:

L. Lévêque, B. Vande Berg, H. Bosmans, L. Cockmartin, M. Keupers, C. Van Ongeval, and H. Liu, "A Statistical Evaluation of Eye-Tracking Data of Screening Mammography: Effects of Expertise and Experience on Image Reading", *submitted to Elsevier Signal Processing: Image Communication*, October 2018.

Chapter 1:
Introduction

1.1 Motivation

Medical imaging involves several scanning techniques to visualise the interior of the human body, along with a representation of the functions of some organs or tissues. Medical imaging provides clinical information either unavailable by other means or with reduced invasiveness, playing a key role in assisting clinicians in diagnosis, treatment planning, and monitoring of patients. Digital medical images are nowadays used in a broad range of medical specialties, including radiology, cardiology, pathology, and ophthalmology [1]. In radiology, for instance, there are approximately one billion imaging examinations conducted worldwide every year. The technologies used to acquire medical images in radiology include X-ray, ultrasound, thermography, computed tomography (CT), magnetic resonance imaging (MRI), positron-emission tomography (PET), single-photon emission computed tomography (SPECT), etc. Both 2D and 3D content may be generated using some of these imaging modalities, as well as video content. Therefore, a large amount of medical visual information is being continuously created, to be viewed or manipulated by medical professionals in their routine practice. Besides radiology, other imaging procedures are commonly applied in diagnosis and treatment planning, such as pathology slides and endoscopic surveys. Furthermore, with the advancements in telemedicine, and particularly in image-guided surgery and tele-surgery [2], images and videos are now being applied in real-time frameworks.

However, medical images are not self-explanatory, i.e., their conclusions are not always obvious. Ultimately, medical images need to be inspected and interpreted by the human eye-brain system. Unfortunately, this interpretation task is not always easy and even competent clinicians can make errors, mainly due to the inherent limitations of human perception. Estimates indicate that, in some areas of radiology, the false negative rate (i.e., when a test result indicates a patient has no disease, and they actually have it) may be as high as 30%, with an equally high false-positive rate (i.e.,

when a test result indicates a patient has a disease, and they actually do not have it) [3]. Therefore, the decisions rendered by clinicians are not always absolutely conclusive [4]. To eliminate errors and improve patient care, it is of fundamental importance to better understand perceptual factors underlying the creation and interpretation of medical images [1], [5] as accuracy is the most important objective in diagnostic imaging practice.

With the advent and growth of imaging technology in medicine, methodologies used to acquire, process, transmit, store, and display images vary and, consequently, the ultimate visual information received by clinicians or other health professionals differs significantly in perceived quality. Visual signal distortions, such as various types of noise and artifacts arising in medical image acquisition, processing, compression, transmission, and rendering, affect the perceptual quality of medical images and potentially impact the accurate and efficient interpretation of images [6]. Quality degradation of medical images often occurs at the acquisition or image post-processing stage. For example, the common sources of MRI artifacts include non-ideal hardware characteristics, intrinsic tissue properties and their possible changes during scanning, and a poor choice of scanning parameters [7]-[8]. In digital radiology using X-rays, common artifacts are caused by under-exposure or over-exposure, collimation issues, and grid use [9]-[10]. CT images are more likely to suffer from artifacts than other radiographs, as the image reconstruction depends on a large number of independent measurements [11]. Finally, in telemedicine, where medical images and videos are being acquired, compressed, transferred, and stored to remotely diagnose and treat patients, various types of compression artifacts and transmission errors, such as blurring, ringing and packet loss, can be produced [12]. Such distortions or artifacts may not preserve essential information for diagnosis and treatment planning. To minimise potential clinical errors caused by visual distortions, and with a view to improve general clinical practice, it is important to understand how medical professionals perceive the quality of medical images and videos through subjective image quality assessment methodologies and statistical data analysis [13].

The human visual system (HVS) is the part of the central nervous system which enables humans to see their environment [14]. Visual attention represents a powerful mechanism of the HVS, which helps the human brain to continuously minimise the

overloading amount of input into a manageable flow of information, reflecting the current needs of the organism and the external demands [15]. In medical imaging, visual attention has been studied in relation to the perception and interpretation of images. Eye-tracking – the process of measuring where people look – has been widely used to record eye movements of image readers, and study how they interact with visual information. Eye-tracking studies have been conducted, for instance, in radiology to reveal how visual search and recognition tasks are performed, providing information that can improve speed and accuracy of radiological reading. Eye-tracking can indeed help with identifying sources of errors [16]. Finally, eye-tracking can also be used to improve training of early career radiologists, as training methods can use gaze training and pattern recognition [17].

1.2 Research questions and objectives

This thesis investigates the following research questions.

- How do compression and transmission visual artifacts affect the perceived quality of medical imaging?
- Does the medical specialty (i.e., radiologists vs. sonographers) affect the quality of visual experience? If so, to what extent?
- How is visual attention allocated for different mammogram views (i.e., cranio-caudal and medio-lateral oblique views) displayed simultaneously?
- Does the specialty (i.e., radiologists vs. physicists) and experience (i.e., experts vs. trainees) affect the gaze behaviour when analysing medical images?

To answer these questions, the following objectives are outlined.

- To quantitatively assess the impact of various factors (e.g., compression, transmission) on the perceived quality.
- To quantitatively assess the impact of medical specialty on the perceived quality.
- To measure and analyse gaze data of mammograms via an eye-tracking experiment.

- To measure and analyse the gaze behaviour of medical professionals with different medical specialty and degrees of experience.

1.3 Thesis structure and contributions

- Chapter 2 gives a detailed introduction of subjective image and video quality assessment in medical imaging, and also introduces the human visual attention and eye-tracking experiments in medical imaging.

- Chapter 3 presents new qualitative and quantitative methodologies developed to assess the perceived quality of medical videos in the particular context of telesurgery. We first performed semi-structured interviews, followed by video quality scoring with expert surgeons. In this chapter, impacts of video content (i.e., scene), compression strategy (i.e., compression scheme and ratio) and transmission (i.e., frame rate and packet loss rate) on perceived quality are studied. Statistical analyses show that compression artifacts and transmission errors significantly affect the perceived quality; and that such effects tend to depend on the specific surgical procedure, visual content, frame rate, and degree of distortion.

- Chapter 4 describes the conduct of a subjective visual quality assessment experiment, aiming to understand the impact of medical specialty, i.e., radiologists versus sonographers, on the perceived quality of hepatic ultrasound videos. The effects of video content and compression strategy on the quality are investigated in this chapter. Results demonstrate that sonographers are more bothered by the distortions than radiologists for highly compressed stimuli, whereas they both have a similar experience with stimuli at lower compression.

- Chapter 5 details the design of an eye-tracking experiment with a large number of cranio-caudal and medio-lateral oblique mammogram views. We conducted a dedicated eye-tracking experiment with radiologists while reading these mammography cases. Their eye movements were analysed to assess the complementary use of these two mammogram views. Results demonstrated

that the medio-lateral oblique view attracts more attention than the cranio-caudal view. Furthermore, we compared existing state of the art computational models of visual attention with the ground truth visual attention data. We evaluate whether and to what extent these models can predict gaze behaviour.

- Chapter 6 presents a large-scale eye-tracking experiment with expert radiologists, trainee radiologists, and physicists, aiming to better understand their gaze patterns when reading medio-lateral oblique views of screening mammograms. This chapter investigates the impact of expertise and experience on gaze patterns. Both gaze duration and gaze deployment show the consistency between expert radiologists, as well as variations between different specialty groups. We also investigated the saccadic behaviour of viewers and illustrated the differences between the groups in terms of saccade amplitudes and orientations.

- Finally, Chapter 7 summarises the outcomes of this thesis and discusses directions for future research, including technological, human, and demographic complexity, as well as an objective approach to study perceived visual quality and visual attention in medical imaging.

Chapter 2:
Background

2.1 Image quality assessment

Despite important improvements in technology and digital imaging, one thing has remained the same over the years and decades, i.e., the human visual system (HVS). The HVS is composed of two functional parts, i.e., the eye and the brain. It can perform a vast number of image processing tasks.

Image quality assessment is therefore critical to control and maintain the perceived quality of visual content. Two different approaches can be considered to assess image or video quality, i.e., objective and subjective evaluations [18]. Objective assessment is based on mathematical algorithms which provide global or local quality measures. This method is reproducible and does not need input of human observers; the main goal of an image or video quality assessment metric is to automatically predict the perceived quality of a content. On the contrary, subjective quality assessment requires observers for a visual study of quality. As human observers are the ultimate receivers of visual information, subjective quality assessment is considered the most reliable approach, particularly in the medical field, where a patient's safety is the priority.

2.1.1 General methodologies

As introduced previously, subjective image quality assessment provides the ground truth on how human observers perceive image quality. The International Telecommunication Union (ITU) established standardised methods for subjective quality evaluation of image and video content. These methods can be divided into two groups: single stimulus methods and multi stimulus methods. A brief description of the representative methods is presented in this section, as well as their merits and drawbacks.

2.1.1.1 Single-stimulus methods

The Absolute Category Rating (ACR) method [19], also called Single Stimulus (SS) method, is a method where test sequences are presented one by one and rated independently on a discrete quality rating scale. The most used scale is the five-level overall quality scale, defined as follows: 1 = Bad, 2 = Poor, 3 = Fair, Good = 4, and 5 = Excellent. This method is easy to implement and allows a quick assessment. However, a large number of observers is needed to obtain satisfactory statistical analysis [20].

The configurations of the Single Stimulus Continuous Quality Scale (SSCQS) method [21] are similar to the ones for the ACR method, but a continuous scale is used in this case, i.e., a 100-point scale cut into five segments: (0-20) = Bad, (20-40) = Poor, (40-60) = Fair, (60-80) = Good, and (80-100) = Excellent.

The Single Stimulus Continuous Quality Evaluation (SSCQE) method [21] is used when the distortions of a video change over time. The score is adjusted in real time by the observer during the whole duration of a video, on a continuous quality scale. The main advantage of this method is to provide the evolution of quality over time. Nevertheless, to use this method.

2.1.1.2 Multi-stimulus methods

The Double-Stimulus Impairment Scale (DSIS) method [19] and the Double-Stimulus Continuous Quality-Scale (DSCQS) method [21] can be defined simultaneously as they present some similarities, i.e., they both employ a deferred presentation of the stimuli. When using the DSIS method, the reference stimulus is presented first, and the distorted stimulus follows. For the DSCQS method, this presentation is repeated a second time. A five-level impairment scale is used for the DSIS method where the score is given for the distorted image, as follows: 1 = Very annoying, 2 = Annoying, 3 = Slightly annoying, 4 = Perceptible but not annoying, and 5 = Imperceptible. The DSCQS method requires the assessment of two versions of each image on a continuous quality scale. Both these methods involve multiple presentations of the original stimuli and therefore require a considerable amount of time for the observers to complete the experiment.

The Stimulus Comparison (SC) method [19], also referred to as Pair Comparison (PC) method, offers a simultaneous presentation of two images or videos side by side. For this method, different distortions of the same content are shown to the observer, who has to choose the one they prefer. The main advantages of this method are that it presents a simple and quick binary choice for the observer and brings reliable statistical analyses [22]. However, this method requires a long time and it can be difficult to watch and compare two videos at the same time.

For the Simultaneous Double Stimulus for Continuous Evaluation (SDSCE) method [21], the reference stimulus and its distorted version are displayed side by side on a monitor. As for the SSCQE method, the quality is evaluated over time on a continuous scale.

Finally, the Subjective Assessment Methodology for Video Quality (SAMVIQ) [23] offers the visualisation of a short video through a graphic interface, where the observer can navigate among the reference and the distorted versions of the content. Each video has to be assessed on a continuous quality scale; the observer has to assess all the different sequences of a content before being able to assess the other contents. This method allows the observer to watch the videos several times and to modify their scores if needed.

2.1.2 Application to medical imaging

In recent years, there has been a growing interest in studying the perceptual quality of medical images and videos. Previous studies have shown that the influence of professional expertise on the assessment of medical image quality is significant, and that experts and naïve observers (i.e., without medical imaging or clinical experience) differently assess the quality of medical visual content degraded with distortions [24]. Psychovisual experiments have been conducted with medical experts assessing the quality of images or videos in various application environments, e.g., in radiology or in the context of telemedicine. Depending on their research question and on the modality chosen, researchers have been using diverse methodologies suggested by the ITU to assess the perceived quality of medical content. In this section, we present an overview of the methods used by diverse research teams, as well as a description of their experimental procedure and results. The aim is to understand how the perception of medical imaging users is affected by specific visual distortions and then use these

results to develop solutions for improved image quality and better image-based diagnosis.

2.1.2.1 Radiology

With about one billion exams performed per year [25], radiology encompasses a wide variety of imaging modalities. In the literature, progress has been made towards the subjective quality assessment of radiology images and videos.

Neri et al. [26] conducted a subjective quality assessment test with cardiologists using the ACR method. The perceptual effects of H.264 [27] compression on echocardiographic and Echo-Doppler sequences were investigated to identify a minimum bit rate that can preserve the diagnostic effectiveness of the ultrasound imaging sequences. Six cardiologists participated in the experiment. The results concluded that a channel capacity of three Mbps is required to preserve the diagnostic effectiveness of the ultrasound sequences.

Suad et al. [28] used the DSIS method to analyse the impact of different common types of distortion (i.e., additive Gaussian noise, blurring, JPEG compression, salt and pepper and sharpness) on brain MR images. A group of fifteen doctors participated in the study, where they were asked to evaluate the quality of one hundred images. Results show that the perceived quality is strongly affected by the distortions, with the highest quality ratio given to sharpness and the poorest to Gaussian noise.

Razaak et al. [29] studied the impact of HEVC (high efficiency video coding) [30] compression on nine medical ultrasound video sequences. The compressed sequences were assessed by both medical experts and non-experts using the DSCQS method. The results were used to analyse the compression performance of HEVC in terms of acceptable diagnostic and perceptual video quality and showed that the level of experience of the experts has an influence on the assessment of diagnostic quality. Moreover, the authors found that an excellent diagnostic quality was obtained up to compression ratio 420:1.

Gray et al. [31] analysed the quality of real time wirelessly transmitted medical ultrasound video, using the DSCQS method. Four ultrasound trained medical professionals rated the quality of videos from eight patients. Using an ANOVA

(Analysis of Variance), the authors showed that the bit rate has a large effect on the quality scores. The results were then used to develop a minimum bit rate threshold to ensure transmitted video is of adequate quality so that physicians may make an accurate diagnosis. The threshold was defined at one Mbps (megabit per second) with H.264 compression for wireless transmission of ultrasound video.

Chow et al. [32] carried out subjective experiments to assess the quality of twenty-five reference MR images of the human brain, spine, knee, and abdomen distorted by six types of distortion (Rician noise, Gaussian white noise, Gaussian blur, discrete cosine transform (DCT), JPEG compression and JPEG 2000 compression) at five different levels. They made use of the SDSCE methodology. The observers, twenty-eight research scholars from the Electrical Engineering department, had to rate the distorted image by judging the differences with the original image. According to the results obtain by t-test, correlations and regression analysis, they declared that Rician noise and Gaussian white noise strongly affect the quality of MR images.

Finally, the impact of a set of common distortions on the perceived quality of brain, liver, breast, foetus, hip, knee, and spine MR images was also studied by Liu et al. [24]. Ghosting, edge ghosting, white noise and coloured noise artifacts were simulated on MR scans with different content and acquisition protocols, for two experiments. The first experiment was divided into two parts: the first one included ghosting and white noise artifacts, while the second included edge ghosting and coloured noise. Five different energy levels were defined for each artifact. In each part, a total of thirty stimuli were shown to fifteen and seventeen expert participants, respectively, using the SDSCE method with a scale from 0 to 100. For the second experiment, a similar procedure was followed with eighteen expert subjects, using the two higher energy levels of all artifacts plus three new variations of the coloured noise, in a total of 112 stimuli. The scores obtained from a one-way ANOVA indicate that artifacts with a flat spectral power density (i.e., white noise and edge ghosting) are nearly twice as bothersome as artifacts with a spectral power density similar to the original image (i.e., coloured noise and ghosting), at the same energy level. The study also concludes that differences in content are very likely to affect artifact visibility and relative impact.

2.1.2.2 Surgery

Psychological studies have also been undertaken in other areas, such as surgery and telesurgery. Most studies conducted focus on laparoscopic surgery, also referred to as "keyhole surgery", which is a type of minimally invasive surgery.

Shima et al. [33] used the DSCQS method to assess four source videos representing different types of cancer in the context of surgical telemedicine. When videos were transmitted over the DVTS (digital video transport system), the quality perceived by eight doctors decreased for pancreatic cancer videos but not for oesophageal, colon and gastric cancers. They also demonstrated that encryption with a VPN (virtual private network) did not degrade the image quality.

Nouri et al. [34] also made use of the DSCQS method on four videos representing different stages of a laparoscopic surgery. Using a regression analysis, the authors found a quality threshold at bit rate of 3.2 megabits per second (or compression ratio 90:1 for MPEG2 compression), below which the surgeons considered the quality too low to perform surgical tasks.

Martini et al. [35] made use of the DSIS (Double Stimulus Impairment Scale) method to evaluate the effects of video transmission errors on two sequences from a biopsy suture. They found that the medical experts scored low quality for all the stimuli, which may be due to the fact that the simulated errors (i.e., various packet loss rates) are annoying and not acceptable for the surgeons.

Chaabouni et al. [36] made use of the DSCQS method on four laparoscopic surgery videos to evaluate the impact of H.264 compression. Fourteen ENT (ear, nose and throat) surgeons participated in the tests. The authors analysed their scores using some correlations coefficients and a regression analysis, and found that compression artifacts could be noticeable from compression ratio 100:1 for H.264 compressed videos.

Another study on H.264 encoded laparoscopic videos was conducted by Münzer et al. [37]. A group of thirty-seven medical experts participated in a double session test, using the DSCQS method to evaluate the impact of resolution and the constant rate factor (CRF) changes on overall image and semantic quality. The results suggested that an acceptable quality may be achieved even reducing resolution down to 640×360

and with CRF = 26. With this set-up, storage requirements drop to 12.5% when compared to current practice.

Finally, Kumcu et al. [38] chose the ACR (Absolute Category Rating) method to assess four abdominal sequences from different surgical procedures. Nine laparoscopic surgeons and sixteen non-experts were involved. Statistical analyses of their scores showed that bit rate of 5.5 Mbps (or compression ratio 111:1 for H.264) was suitable for a surgical procedure, whereas bit rate of 3.2 Mbps (or compression ratio 214:1) was too poor to conduct a surgery.

2.1.2.3 Other modalities

Subjective image and video quality assessment experiments have also been conducted in other medical areas, including, but not limited to: pathology, ophthalmology, endoscopy, and 3D images.

Tulu et al. [39] studied the effects of delay, jitter, and packet loss ratio (i.e., network impairments) on ophthalmology videos in the context of telemedicine, using the SSCQS method. With an ANOVA, they found a significant effect of jitter for high-movement videos. Furthermore, they showed that the perceived quality does not only depend on technical parameters such as jitter and delay, but also on critical frames, i.e., the frames which allow making a diagnosis, as they play a decisive role for the viewer.

Platisa et al. [40] investigated the effects of blurring, colour, gamma parameters, noise, and image compression on animal digital pathology images (dog gastric fundic glands and foal liver). For that, they conducted an image quality assessment evaluation with six veterinary pathologists, seven veterinary students, and eleven imaging experts using the Single Stimulus Hidden Reference Removal (SS-HRR) method with a six-point ACR scale. Using median opinion scores and Kruskal-Wallis non-parametric one-way analysis of variance, they observed the disagreement between the quality ratings made by different expertise groups, warning against guiding the development of any pathology specific image algorithms or imaging systems by psycho-visual responses of subjects who are not experts in pathology.

Kara et al. [41] made use of the ACR method with a view to study the angular resolution and the light field reconstruction on 3D heart images. They chose a ten-

point scale for their tests and recruited twenty observers, eight medical experts and twelve non-experts. Thanks to a regression analysis, results showed that observers are more sensitive to degradations in texture than to a lower number of views.

Finally, Usman et al. [42] assessed the impact of the quantization parameter (QP) in both visual and diagnostic quality of HEVC compressed videos from wireless capsule endoscopy using the DSCQS. A total of twenty-five observers participated in the study, consisting of nineteen non-expert and six medical expert observers. Experimental results, analysed with correlations, recommended QP threshold values of 35 and 37 in order to provide satisfactory diagnostic quality and visual quality, respectively.

2.1.3 Summary points

2.1.3.1 Single-stimulus vs. multi-stimulus methods

As we noticed from the studies presented previously, both single- and multi- stimulus methods can be used for subjective assessment of perceptual quality of medical images and videos that differ in acquisition modalities, such as ultrasound, surgery, pathology, etc. Each methodology has claimed advantages. Experiments conducted using single stimulus methods are usually quicker to conduct than with double stimulus methods, and they avoid potential vote inversions as only one stimulus is rated at a time [43]. However, single stimulus experiments may lead to a score drift over the course of a session [44]. New methods have therefore been defined, such as the SAMVIQ method, which allows observers to re-view the reference and re-evaluate their scores.

2.1.3.2 Influential factors

The standardised methods as mentioned above, i.e., single- and multi- stimulus, are widely used to assess the perceived quality of natural visual content under natural viewing conditions. However, the use of these methods for the assessment of medical images and videos remains an open-ended question. It should be noted that clinical practice is rather complex, and issues such as how medical experts perceive video quality aspects remain largely unexplored. The perceptual quality of medical images and videos can be affected by many different influential factors (IFs), which can be grouped into three categories [45]: system IFs, context IFs, and human IFs.

The methods used for subjective assessment of medical content usually take into account the system IFs, which refer to properties and characteristics that determine the technically produced quality of medical image and video. There are four types of system IFs: content-related IFs, media-related IFs, network-related IFs and device-related IFs. In subjective assessment of the perceptual quality of medical images and videos, content-related IFs consist of content type, media-related IFs include all media configuration factors, while network-related and device-related IFs refer to all network and device parameters that affect the perceptual quality, respectively. Since content-related and media-related IFs are interlaced, they can be discussed jointly. Many research studies introduced in the previous section dealt with content and media-related IFs (e.g., distortion type, scene, bit rate, resolution, encryption), whereas the network-related IFs (e.g., delay, jitter, packet loss) have not received as much focus. Moreover, there is no evidence that device-related IFs have been considered in subjective assessment of perceptual quality of medical contents. Content and media-related IFs are manipulated at different levels in order to conduct various statistical analysis that describe their impact on the perceptual quality of medical images and videos.

In subjective user studies, the perceived quality of medical contents may vary with viewing environments which have different context IFs. They refer to any situational properties of the environment of medical images and videos that have an impact on perceptual quality. The most important context IFs are physical, temporal and task/social IFs. Although many subjective studies are conducted in different environments and under various conditions, methods for subjective assessment do not consider them as physical or task context IFs. In this sense, different numbers of medical observers are usually asked to watch and evaluate the perceptual quality of medical contents in a single-tasking situation without taking into account a large number of other context IFs. Therefore, a deeper and more comprehensive analysis of context IFs is required to properly assess the perceptual quality of medical content, such as applications (e.g., diagnosis, surgery, training), clinical factors (e.g., emergency care, lesion suitableness), requirements (e.g., real-time/offline, location), medical data (e.g., clinical information, anatomical, functional, physiological), acquisition modalities (e.g., ultrasound, X-Ray, MRI), and data types (signal, images/videos, monochrome/colour) [12].

The perceptual quality of medical contents may also be affected by human IFs, which refer to any properties or characteristics of the human user that influence his/her perception of quality. Human IFs can generally be classified into two categories, i.e., low-level processing IFs (e.g., physical, emotional and mental constitution of human), and high-level processing IFs (e.g., demographic and socio-economic background). Based on the literature review presented, one may notice that there are almost no subjective user studies considering the impact of the low-level processing human IFs (e.g., emotional state of the medical observer) on the perceptual quality of medical images and videos. The number and expertise domain of the subjects, which is are important high-level level processing human Ifs, were usually taken into account when conducting subjective tests.

The number of assessors (i.e., medical observers) varies between studies. One can argue that the availability of medical experts is determinant. The domain of expertise of the assessors encompass: radiologists (specialised in medical imaging and trained to interpret the scans to help in making a diagnosis), specialists (specialised in diagnosis and treatment of a particular organ), surgeons (specialised in surgery with more anatomical knowledge and its clinical relevance), etc. Zhang et al. [46] asked four radiologists and eight naïve observers to complete a task of the detection of abnormality. Results showed that radiologists have a better ability to detect hyper-signal than naïve observers. In their study on the quality assessment of compressed laparoscopic videos, Kumcu et al. [38] asked surgeons and non-experts to rate the overall quality of twenty sequences. Their first observation was that the subjective median scores were correlated between experts and non-experts with a Spearman correlation score of 0.83. Their second remark was that the surgeons have an ability to appreciate the specific anatomical structures when assessing the quality, while non-experts were insensitive to the content when evaluating the effects of compression. Kumcu et al. suggested that non-experts should not be used as surrogates of surgeons for quality judgment. According to the above-mentioned experiments, we may conclude that the expertise of assessors must be carefully considered during the preparation of the subjective experiment in the medical context. Nevertheless, non-medical or naïve assessors could be involved, if no-prior medical knowledge is required for certain applications (such as a pre-assessment task or a supplementary test).

All this suggests that conventional methodologies may require modifications when applied to medical images and videos. Attempts to adjust and refine experimental methodologies have been made by Shima et al. [33] and Kumcu et al. [38] where practical aspects (e.g., “suitability for surgery” and “usefulness”) had been considered and integrated into conventional quality scoring tasks. Similarly, in [47], Kowalik-Urbaniak et al. intended to find out the degree to which a medical image can be compressed, using JPEG or JPEG2000 algorithms, before its quality is compromised. A set of ten compressed CT images were presented to two radiologists, who were requested to rate the quality of an image using a binary scale, i.e., acceptable or unacceptable. In the experiment, the radiologists were instructed to flag an image as unacceptable in the case they believed there was any noticeable distortion that could have any impact on diagnostic tasks. Results indicated that compression ratio was not always a correct measure for visual quality.

2.1.3.3 Statistical analyses

Furthermore, when conducting subjective experiments, some observers may report dubious scores. This can be due to misunderstanding the instructions or to a lack of engagement in the task [48]. It is thus recommended to use an outlier detection and subject exclusion procedure, presented in ITU-R recommendation BT.500-11 [21].

Subjective experiments with medical images and videos present different characteristics than experiments conducted with natural content, due to the distinctive nature of medical imaging. In a medical context, it is particularly important to test whether participants are consistent in their quality scoring, as their years of experience in medicine may affect their perception of visual distortions [49]-[50]. Therefore, it may appear necessary to divide observers into groups depending on their experience and/or specialty, as it has been done by some of the studied research teams. A common way to analyse the impact of the participants on scoring is to conduct an ANOVA on the scores. Indeed, the ANOVA is used to compare the means of two or more independent samples when assuming normality and homogeneity of the variance.

Two other main analyses were used in the studied articles: correlation and regression analysis. Correlation is often used to study whether two variables are correlated and the strength of this relationship. Contrary to correlation, regression allows to predict one variable from another. However, it can be noted that these analyses were not used

for the same purpose. Indeed, the correlation coefficients have mostly been used to evaluate the relationship between existing image quality metrics and the human scores obtained.

2.2 Eye-tracking in medical imaging

Eye-tracking is a widely used method which enables to record eye positions and eye movements of a human subject. In fact, eye movements allow a deeper insight into human attention, even revealing their needs and emotional states for instance [51]. The phenomenon of human visual attention has been studied for over a century, with the objective of understanding how human brain continuously minimises overloading amount of input into a manageable flow of information. Significant findings were established in literature that visual attention is essentially driven by two general attentional processes, i.e., bottom-up and top-down [52]. Bottom-up aspects are based on characteristics of the visual scene, making it stimulus driven. Regions of interest that attract attention in a bottom-up way must be sufficiently distinctive with respect to surrounding features [53]. On the other hand, top-down attention is driven by factors such as knowledge, expectation and experience.

Eye-tracking, and more particularly the measurement of the point of gaze, has emerged as the key means of studying visual attention. The origins of eye-tracking date back to 1879 when French ophthalmologist Louis Emile-Javal noticed, based on naked-eye observations, that readers' eyes make quick movements (i.e., saccades) mixed with short pauses (i.e., fixations) while reading. The first eye-tracker, which was an intrusive device, was built in 1908 by Edmund Huey. The first non-intrusive recordings of eye movements were conducted by Guy Thomas Buswell, an educational psychologist, in 1937 [54]. During the 1970s and 1980s, video-based eye-trackers were invented to enable less intrusive and more accurate eye-tracking practice. Nowadays, it is used in a wide range of applications, including cognitive psychology, marketing research, usability engineering, human computer interaction, and medical image quality [55]. An eye-tracking study usually involves the participation of a certain number of human subjects, the recording of their eye movements using a sophisticated eye-tracker, and the agglomerated analysis of their fixation/gaze patterns.

In recent years, there has been a growing interest in the use of eye-tracking technology in medical imaging. In radiology for example, eye-tracking methodologies have been widely used to study how visual search and recognition tasks are performed, providing information that can improve speed and accuracy of radiological reading. Generally, in a typical eye-tracking study, a target stimulus is presented to a sample of image readers while their eye movements are recorded by an eye-tracker. The resulting eye-tracking data is then statistically analysed to provide evidence of the subjects' visual behaviour. This information can be subsequently used to assess the image quality of diagnostic imaging systems and to improve task performance of medical professionals. Also, it would be highly beneficial for image readers to have a tool that can automatically and accurately predict where experts look in images. This can be used as an automated perceptual feedback system to enhance their diagnostic performance.

In this section, we present a comprehensive literature review that focuses on eye-tracking studies in medical imaging.

2.2.1 Visual search patterns

Visual search patterns in medical imaging can be extremely complex due to their important outcomes, e.g., the detection of a particular disease. This is why it is crucial to identify visual search patterns associated with accuracy and precision.

In 1981, Carmody et al. [56] published one of the first eye-tracking studies where visual search was investigated by means of eye-position recording techniques. They studied the detection of lung nodules in chest X-ray films. Four radiologists participated in the experiment, where they were asked to search for nodules in ten chest films. Their eye movements were recorded using special glasses based on corneal reflection technique. Subjects were instructed to press a key when they found a nodule in the X-rays. The eye-tracking data, i.e., visual dwell times, were used to analyse visual search behaviour. It was found that false negative (i.e., omission) errors were impacted by both the visibility of the nodule and the scanning strategies used by the radiologist.

A decade later, Beard et al. [57] conducted an eye-tracking study using an Eye Mark Recorder (model V) to understand visual scan patterns developed by radiologists when

interpreting both single chest and multiple abdominal CT scans. Four radiologists and one radiology resident participated in the first part of the study where single CT scans were tested. Their task was to read and interpret three patient cases, each of which contained 30 to 40 image slices. Radiologist scan patterns were rendered manually from the tape records; and a systematic sequential visual scan pattern was found. The second part of the study was to assess how images were cross compared, using multiple CT scans. The radiologists had to view three patient folders each containing more than one CT scan with the number of films exceeding the available viewing space. Eye-tracking data showed that the radiologists used a similar approach of reading single CT scans, i.e., a systematic sequential visual scan, however, they also developed a comparison method.

Suwa et al. [58] also carried out a study with CT images, but in the field of dentistry. They recruited eight dentists, and each was shown ten normal and ten pathologic CT images. Eye movements of the dentists were recorded with an eye-tracking system (model 504) when interpreting the images. Six parameters were extracted from the eye-tracking data: time to determine whether the image is normal or pathologic, fixation point count, distance between fixations, time spent on each fixation, total gaze fixation time, and minimum gaze fixation time. Based on these parameters, the gaze patterns of dentists were investigated. Considering the difference in gaze patterns between normal and pathologic images, it was found that when viewing a normal image, the subjects tended to move sequentially (as noticed by Beard et al. [57]), whereas, when viewing a pathologic image, the tendency was to focus on suspected regions. Moreover, they found that both the travel distance between fixations and the minimum gaze fixation time were longer for pathologic images than normal ones. The total gaze fixation time, which is shorter for normal images, significantly contributed to determine whether an image was normal or pathologic.

Eye-tracking studies were also conducted in other medical specialties, such as mammography. Kundel et al. [59] gathered eye-tracking data collected independently at three institutions with an ASL (Applied Science Laboratories) eye-tracking device, where experienced mammographers, mammography fellows, and radiology residents searched for cancers in mammograms, both on craniocaudal and mediolateral oblique views. They found that 57% of cancer locations were fixated within the first second of viewing. They concluded that the initial detection occurs before visual scanning and

that the development of expertise may consist of a shift from scan-look-detect to look-detect-scan mechanism.

Voisin et al. [60] also worked on mammogram images. They investigated the association between gaze patterns and diagnostic performance for lesion detection in mammograms. They recorded the eye movements of six radiologists while evaluating the likelihood of malignancy of forty mammographic masses, using a Mirametrix S2 eye-tracker. By assessing various quantitative metrics derived from the eye-tracking data, such as the fixation duration, number of fixations, and fixation/saccade ratio, they showed that these gaze metrics were highly correlated with radiologists' diagnostic errors. For instance, a long review time leads to a high chance of error.

Almansa et al. [61] investigated the relationship between gaze patterns captured with an ASL mobile eye-tracking device and adenoma detection rate in colonoscopy videos. Eleven endoscopists participated in a study in which they were asked to watch three high-definition video clips from three normal colonoscopies. Diverse forms of information were gathered from the eye-tracking data, including total gaze time, number of fixations, and mean duration of fixations. The results showed that the adenoma detection rate was significantly correlated with the central gaze time, i.e., time spent on the centre of the screen. It was found that the participants who detected the highest number of adenomas showed a tendency to focus on the centre of the screen, whereas participants who detected less lesions moved their eyes more broadly.

Drew et al. [62] worked on 3D CT images. Twenty-four radiologists were recruited to search for lung nodules in chest CT scans. Five cases were used, and there were fifty-two nodules in total. The radiologists were asked to find as many nodules as possible in three minutes (note false positives were deleted from the database). Based on the eye-tracking data collected using an EyeLink1000 eye-tracking device, Drew et al. divided the radiologists into two groups depending on their reading strategies: "scanners" and "drillers". Scanners usually search throughout a slice in depth before moving to a new depth, whereas drillers limit their search to a part of the lung while scrolling through slices in depth. In general, drillers found more nodules than scanners.

2.2.2 Influence of experience and expertise

With a view to improve the diagnostic performance of medical students, it is necessary to understand how they perceive medical images and then to compare their viewing behaviour with that of medical experts. Existing eye-tracking studies that compare viewing behaviour of experts and novices can be divided into two categories: studies on medical diagnosis and studies on surgery. We will discuss each category in detail below.

2.2.2.1 Diagnosis

This section is looking at studies that compare experts and novices when rendering diagnoses based on diverse modalities of medical imaging, including, but not limited to CT, MR, and radiographs.

Nodine et al. [63] carried out an eye-tracking experiment where participants (i.e., three mammographers and six radiology trainees) were asked to view forty mammogram cases and decide whether they were "normal" or "abnormal". Their eye movements were recorded using an ASL4000 eye-head tracker. Experimental results showed there was no significant difference in terms of decision time between experts and trainees, however, mammographers' performance was always higher than trainees'. The eye-fixation patterns of trainees were compared to that of experienced mammographers; and the results indicated that trainees did not spend enough time on the lesions.

Similar findings were obtained in the study of Tourassi et al. [64], where three breast imaging radiologists and three residents were asked to view twenty screening mammograms for a specific task of mass detection while wearing a H6 head-mounted eye-tracker. In consistence with the study of Nodine et al. [63], the residents' detection accuracy was on average lower compared to the experts. The recall rate of residents and expert radiologists was nonetheless the same on average. The results also showed that radiologists possess a more complex gaze behaviour than residents.

There are few studies that focus on CT images, such as Cooper et al. [65], Matsumoto et al. [66], Bertram et al. [67]-[68], and Mallett et al. [69]. Cooper et al. [65] investigated visual search behaviour on stroke images with three experienced readers, one trainee and four novices. Participants were asked to rate eight clinical cases on a five-point Likert scale, depending on the presence or absence of abnormality and their

degree of confidence. The results showed a significant difference in diagnostic accuracy between novices and experts; the experts performed better than the novices. Recorded eye-tracking data were used to reveal the reasoning behind the observed difference between novices and experts. In case of an acute stroke, the trainee reader noticed the region of interest with the 34th fixation whereas the experts fixated in with their first fixation. For a chronic stroke case, novices only spent a short time looking at the affected area, and experts concentrated on the affected tissue from the first fixation. Matsumoto et al. [66] also studied stroke cases two years later, with twelve neurologists and twelve control subjects consisting of nurses, medical technologists, psychologists, and medical students. Findings proved that both neurologists and control subjects gazed at visually salient areas in the images, however, only neurologists gazed at visually low-salient areas with clinical importance. Bertram et al. [67]-[68] applied the approach of the two aforementioned studies to abdominal CT images. In their first study [67], they compared the eye movements of seven radiologists, nine radiographers and twenty-two psychology students when watching abdominal CT scans. Participants had to perform an easy task, i.e., detecting visually salient abnormalities, and a difficult task, i.e., detecting enlarged lymph nodes. Results showed that for the difficult task, experts performed better than semi-experts and naïve participants; however, there was no difference in detection performance between semi-experts and novices. For the easy task, experts and semi-experts performed better than naïve participants. In the second study [68], Bertram et al. investigated markers of visual expertise using twenty-six abdominal CT images. An eye-tracking experiment was conducted with twelve specialists, fifteen advanced residents and fifteen early residents when performing a detection task. Similar to their first study, they found that the detection rate of specialists was higher than that of residents, and that advanced residents detected more lesions than early residents. On average, eye-tracking data showed that specialists reacted to the presence of lesions using long fixation durations and short saccades. Finally, Mallett et al. [69] focused their study on twenty-three 3D CT colonography videos, which were interpreted by twenty-seven experienced and thirty-eight inexperienced radiologists. Experimental results showed that experienced readers had a higher rate of polyp identification than inexperienced readers, but there was no difference between the two groups in terms of percentage of pursuits and total assessment period. Eye-tracking data revealed that readers examined polyps by multiple pursuits, meaning that they recognised the importance of the

lesions. There was no difference regarding the rate of scanning errors between experienced and inexperienced readers.

The scope of eye-tracking studies was broadened by Manning et al. [70], Leong et al. [71], Vaidyanathan et al. [72], and Turgeon et al. [73], for radiographs, chest images, dermatological images, and panoramic images, respectively. Manning et al. [70] analysed the gaze behaviour of eight experienced radiologists, five experienced radiographers (before and after training) and eight undergraduate radiography students when detecting nodules, with an ASL504 remote eye-tracking device. They showed that the radiologists and radiographers after training were better at performing the task than the novices, and that the novices and radiographers before training made more fixations per film. In the study of Leong et al. [71], they recruited twenty-five observers with different specialisation who had to examine thirty-three skeletal radiographs and identify fractures. Their eye movements were recoded using a Tobii 1750 eye-tracker. Results showed that there was no significant difference between the groups in the time spent on evaluating the radiographs. However, the experts had a higher number of true positives. Vaidyanathan et al. [72] compared the eye movements of twenty-two dermatology experts and twelve undergraduate novices when viewing thirty-four dermatological images. As a result, they found that experts can weigh a region's importance after a brief fixation, whereas novices need multiple re-fixations. Moreover, they discovered that the median fixation duration and saccade amplitude are significantly higher for experts than for novices. Finally, in a more recent study, Turgeon et al. [73] used twenty dental panoramic images to assess the influence of experience on eye movements with a SMI RED-m device. They asked fifteen oral and maxillofacial radiologists and thirty dental students to view freely the images, while their gaze movements were recorded. They found that all participants spent more time on normal images than abnormal images. Radiologists needed less time before making their first fixation on the region of interest, and they made fewer fixations than the students on images of pathoses.

To summarise, the findings from different eye-tracking studies showed that experts and novices have different gaze behaviours when making diagnoses based on medical images. Novices should be trained in order to reach the experts' level characterised by a particular gaze behaviour.

2.2.2.2 Surgery

This section examines studies that compare experts and novices when evaluating surgical images or videos.

Law et al. [74] were the first researchers to investigate gaze behaviour between experts and non-experts for laparoscopic surgery in 2004. They believed that there would be distinctive characteristics in gaze between the two subject groups. Law et al. conducted an eye-tracking experiment with five expert surgeons and five students, where subjects had to perform a virtual task: they were asked to touch a small target using a virtual laparoscopic tool, as quickly as possible and without committing an error if possible, for two blocks of five trials each. Eye-tracking data were collected using an ASL 504 remote eye-tracking device. Results showed that the experts performed significantly better than non-expert participants, both in time and precision. In terms of visual behaviour, novices spent more time looking at the tool than the experts.

Kocak et al. [75] then recorded the eye movements of eight novices, eight intermediates and eight experts in surgery with a Cyclops Eye Trak saccadometer when performing three basic laparoscopic tasks, i.e., loops, rope and beans. The results showed that the degree of experience affected the fixations and saccades. The average saccadic rate was significantly higher for novices than the experts. Furthermore, the duration of fixations was higher for the expert group than the intermediate group and the novice group.

In 2010, Ahmidi et al. [76] published their eye-tracking study on laparoscopic surgery. They recruited five expert surgeons and six novices who had to find a given anatomy in the sinus cavity and touch it using an endoscope. Their work showed that the surgeons' gaze data included skill related structures, which were, however, not found for novices. They also presented an objective method to assess the expertise level of surgeons using the Hidden Markov Model.

At the same time, Richstone et al. [77] published their study, in which twenty-one surgeons participated in a simulated and live surgery where they had to achieve different tasks of varying degrees of difficulty. Their eye movements were recorded using an EyeLink II eye-tracker. Quantitative metrics related to eye movements, such as blink rate, fixation rate, pupil metric and vergence were evaluated. Their work

demonstrated that, for both simulation study and live surgery, eye metrics made a distinction between non-expert and expert surgeons in a reliable way.

Finally, Khan et al. [78] studied the eye movements of surgeons when performing a surgical task and later on when watching the operative video, as well as the gaze of surgical residents. Two expert surgeons and twenty novices were recruited for the eye-tracking study using a Tobii X50 device. Sixteen laparoscopic cholecystectomy cases were used. The results showed that there was a 55% overlap for expert surgeons between "doing" and "self-watching", and only 43.8% for junior residents. The difference between the two groups is statistically significant.

All eye-tracking studies available in literature focus on laparoscopic surgery, which is a type of minimally invasive surgery. This practice is of benefit to patients due to the reduced incisions and recovery time. Findings with regards to the impact of expertise in gaze behaviour largely coincide with those in radiology studies.

2.2.3 Impact of training on viewing behaviour

In the previous section, differences between medical students and experts were discussed in terms of their viewing behaviour. The next step is therefore to improve training, so that trainees become, in turn, experts. In this section, eye-tracking studies assessing the impact of training on the viewing behaviour of medical professionals are presented.

As mentioned previously, expert surgeons tend to focus on their task whereas novices follow the tool during laparoscopic surgery. Wilson et al. [79] developed further research to study the effect of training on gaze behaviour in laparoscopic surgery with an ASL mobile eye-tracking device. Thirty medical trainees with no previous laparoscopic training participated in the experiments. They were divided into three equal groups, and each group received a different training program, i.e., gaze training, movement training, or discovery training. The first group was shown a video of an expert's eye movements when performing a coordination task. The second group was shown the same video but without the gaze cursor. Finally, the third group was given no video or instructions but was allowed to examine their own performance. Before training, statistical analyses showed no significant difference between the three groups in terms of completion time. After training, the results proved that the gaze group was

significantly faster than the movement group and the discovery group. Furthermore, the gaze group spent significantly more time than the other two groups using target locking fixations, i.e., fixations spent on the target ball and not on the tool. It is suggested that neural mechanisms in charge of goal-directed movements benefit from the foveated target [80].

Vine et al. [81] conducted a similar study to assess the impact of gaze training in laparoscopic surgery; however, in contrast to the study of Wilson et al. [79], the participants were not made aware of the objective of the training. Twenty-seven participants who had not received any laparoscopic training were involved in the study. They were assigned to a gaze training group or to a discovery learning group. Each participant had to complete a task, i.e., to move foam balls into a cup using a single instrument. The first group was shown a surgery training template to passively adopt experts' gaze patterns, whereas the second group did not use a template. There was no significant difference between the two groups before training. After training, statistical analyses revealed a significant difference between the two groups in terms of completion time and accuracy. The gaze training group completed the task more quickly and was in general more accurate than the discovery learning group.

It should be noted that laparoscopic surgery is not the only field where the impact of training was assessed based on eye-tracking. For example, Krupinski et al. [82] studied the impact of training on viewing behaviour in pathology with an ASL SU4000 device. They followed four pathology residents over time during their training, i.e., once a year for four consecutive years. Each time, the residents had to select the top three locations they would like to zoom into in twenty breast core biopsy surgical pathology cases. The fixation positions were recorded, and the dwell time was calculated for each fixation. Statistical analyses showed that the residents became more efficient with training, and generated fewer fixations as well as revisited fewer locations.

Chapter 3:
How do medical professionals perceive video quality?

3.1 Introduction

Telemedicine refers to "the use of information and communications technologies (ICT) to provide and support clinical healthcare at a distance" [83]. The ultimate goal of telemedicine is to improve the accessibility, efficiency, and effectiveness of clinical processes utilised by healthcare organisations, practitioners and patients. Telemedicine is being conducted to optimise medical resources and compensate for the lack of healthcare provision in places where the number of medical professionals relative to the size of the population is very small and access to advanced healthcare is limited. As a result, the use of telemedicine offers a transformative opportunity for access to and delivery of high-quality healthcare in resource-poor settings, particularly, but not exclusively, in rural areas.

There are four recognised acts of telemedicine, namely tele-consultation, tele-expertise, tele-monitoring and tele-assistance [83]. Tele-consultation involves a remote consultation between a doctor and a patient, which is often conducted via telephone or videoconference. Tele-expertise is concerned with communicating a remote request of clinical advice between medical professionals, such as seeking a second opinion on image-based diagnosis off-line. Tele-monitoring enables medical professionals to remotely interpret pre-recorded medical data of patients. Tele-assistance is used to allow a clinical expert to support other clinical professionals during a medical intervention, which is the topic to be investigated in this chapter.

In principle, tele-assistance is conducted in more demanding situations, where the success of the practice partially depends on the effectiveness of the transmission of medical videos in real time. Recently, telesurgery (also known as remote surgery), has emerged as a prevalent form of medical tele-assistance, where the clinical practice involves an expert surgeon assisting a remote (less-experienced) surgeon to complete

a surgical procedure [2]. It is useful in case of a shortage of experienced professionals, and benefits healthcare services in terms of timely surgery for patients, reduction of costs, and training of young surgeons.

The implementation of telesurgery would not have been possible without the support of modern digital image and video communication systems. Unfortunately, these systems generate, as a side effect, various types of distortion in visual signals, such as visual impairments caused by lossy data compression and transmission errors due to bandwidth limitations [84]. Therefore, the ultimate visual content received by the end user largely differs in perceived quality, depending on the system and its applications. The visual distortions can affect viewers' visual experiences and, consequently, may impact the practice of telesurgery, and thus risk the patient's health. Being able to maintain, control and improve the quality of medical videos has become a fundamental challenge in the design of telesurgery systems [13].

In this chapter, we describe interviews carried out with abdominal surgeons from Angers University Hospital in France. A controlled experiment was then designed and conducted based on a better understanding of the context of telesurgery, thanks to the qualitative data collected during the interviews.

3.2 Semi-structured interviews: relating quality in the context of telesurgery

3.2.1 Protocol

In order to better understand quality perception in the context of telesurgery, we carried out qualitative research through interviews – an important gathering technique involving verbal communication between the researcher and research subject [85]. Interviews can be structured or semi-structured. For a structured interview, a rigorous set of questions is prepared prior to the interview and usually allows a limited number of answers. A semi-structured interview is more open (i.e., allowing informants the freedom to bring up ideas or express their views during the interview), but with a list of specific topics of interest being thought about well in advance which have to be covered. These interviews are used to collect data on a particular topic [86]. Semi-structured interviews are widely used in qualitative research to provide reliable and

comparable qualitative data [87]. We used semi-structured interviews to reveal all relevant aspects of the image quality assessment problem, including purpose, context, and meaning, to get preliminary information linked to the quality attributes present in the videos.

Knowledge management is a methodology commonly used to conduct semi-structured interviews. The principle of knowledge management is to make the know-how of experts explicit (i.e., the transition from a tacit know-how to explicit knowledge) [88]. CTA (Cognitive Task Analysis) [89] is a knowledge capitalisation method whose purpose is to elicit knowledge and skills used by an expert during a task involving a strong cognitive activity (such as making a decision, solving a problem, and being aware). This method is made of five steps: collection of preliminary knowledge, identification of knowledge representations, application of knowledge elicitation methods, analysis of acquired data and formatting results. This method is the extension of traditional task analysis techniques to underline goal generation, decision-making and judgments [90], which are essential to study image quality assessment in the context of telesurgery.

As recommended by the CTA methodology, a literature review was made on the topic of interest (i.e., telemedicine and surgery) to set up the interviews. We then made a list of questions and topics to be explored with the surgeons. The topics can be divided into two categories: telemedicine and field of expertise on the one hand, video quality on the other hand. The questions asked are: ‘What do you generally expect in a setting of telesurgery?’; ‘What are the most important aspects you would look for in this type of exam?’; ‘What is the most challenging part of this procedure?’; and ‘What are the necessary knowledge and materials for the conduct of such a procedure?’. Three surgeons were interviewed, and each interview lasted approximately one hour. During each interview, several videos of abdominal surgery (i.e., open and laparoscopic surgeries) were shown. These videos were pre-captured in Angers University Hospital, with a Sony Handycam HDR-CX280 model for open surgeries and a Stryker’s endoscope for laparoscopic surgeries. All interviews were tape-recorded.

3.2.2 Results

The recordings of the interviews were analysed using Strauss and Corbin's coding methodology [91], which is widely used in the literature to analyse qualitative data. It consists of the following stages: gathering qualitative data (i.e., semi-structured interviews), organising the data (i.e., transcribing), fragmenting the data (i.e., open coding), categorising the data (i.e., axial coding), and linking the data (i.e., selective coding).

After transcribing the interviews, every sentence was analysed using open coding. The similar open codes were then grouped into categories to define the axial codes. To achieve this step, keywords and key ideas were first grouped using synonyms or lexical fields, and then into concepts. Finally, two core concepts were defined during the selective coding: information about medical tele-assistance in general and information more specifically linked to the video characteristics. Tables 3.1 and 3.2 represent the key concepts defined from the interviews. All the elements are detailed further.

Table 3.1: Generalities on telesurgery defined from the interviews.

Concepts	Axial codes	Open codes
Use	Remote assistance	Critical phases
		Second opinion
	Teaching	Future surgeons
Requirements	Patient clinical case	Context
		Drug history
		Potential problems
	Visualisation	Quiet room
		Low light conditions
		Large screen

In terms of the clinical environment of the telesurgery practice, surgeons do not need assistance during the whole procedure but only for critical phases. To help a remote surgeon, the expert must know the degree of emergency of the procedure, and the

surgeon's level and potential difficulties. They also need information about the clinical case of the patient, such as context, medical history and drug therapy. Finally, the expert has to be in a quiet room with low light to watch the videos, like in routine clinical practice.

Table 3.2: Video characteristics information from the interviews.

Concepts	Axial codes	Open codes
Image	Features	Centre
		Colours
		Contrasts
		Edges
		Textures
	Shooting	Abdominal cavity for open surgery
		Whole scene for laparoscopic surgery
Video	Transmission	Real time
	Audio	Real time
		Both ways

In terms of the perception of video material, experts only watch the central area of the picture during a surgical procedure if acquisition was correctly made; therefore, it can be inferred that distortions at the periphery of the picture are less inconvenient than those in the centre. Experts can approximate the size of the organs by comparing them to the instruments. Some elements appeared to be very important to locate the organs, such as colour, edge, texture, and contrast. These attributes have to be of a sufficient quality in the context of remote assistance in surgery. A point was raised during each interview that the sound and interaction were essential. However, this point is considered outside of the scope of our study.

For open surgeries, experts do not need a video of the operating room but only of the abdominal cavity, whereas a video of the whole scene is necessary for laparoscopic surgeries because the trocars have to be correctly positioned. For laparoscopy, both videos (i.e., the abdominal cavity and the scene) are not needed at the same time. We also learned some additional information during the interviews. Indeed, during a

planned surgery, a surgeon can take a break of up to four to five minutes if there is a technical problem during video transmission (e.g., Internet disruption). Laparoscopic surgery is never used for emergency cases whereas open surgery can be.

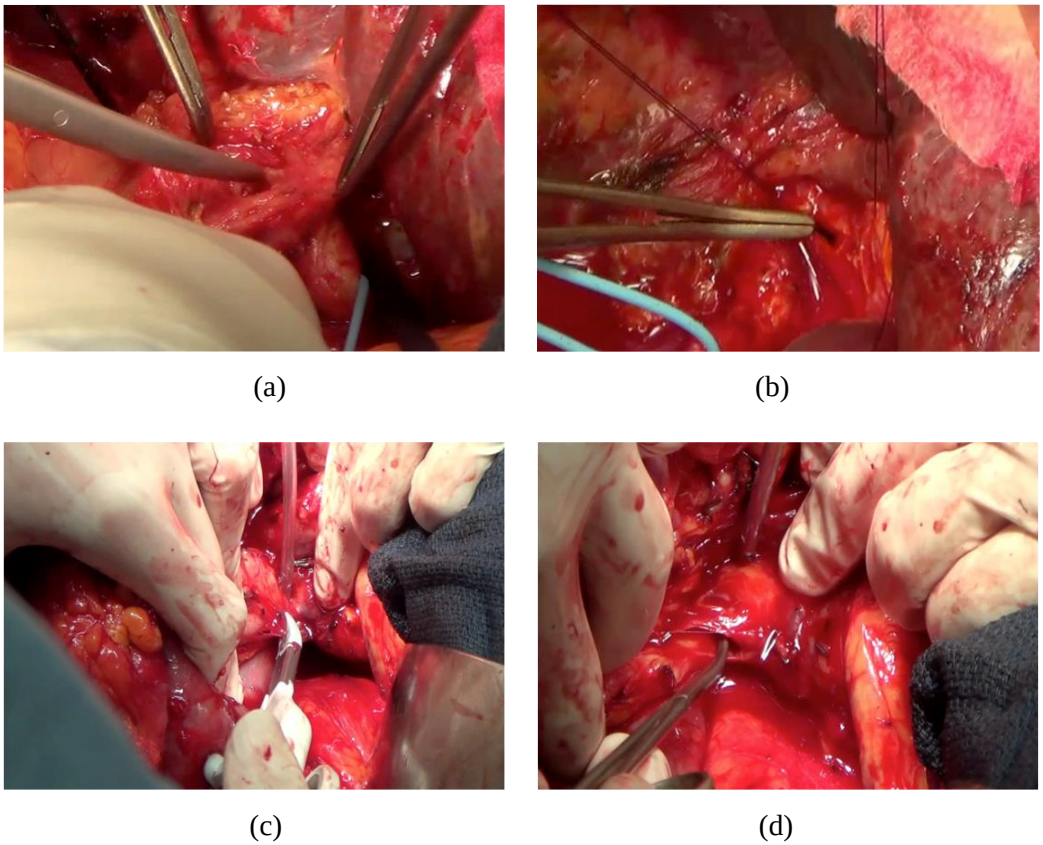
The results of the semi-structured interviews are used to develop a new experimental design for the subjective assessment of video quality in the context of telesurgery, which is detailed below.

3.3 Controlled experiment: rating quality in the context of telesurgery

3.3.1 Methodology

For each type of surgical procedure, namely open and laparoscopic surgeries, four relevant videos of twenty seconds each were extracted from real surgical acts by a senior surgeon from Angers University Hospital who did not participate in the later stages of the subjective experiment. The choice of these excerpts was justified by the model created as a result of the semi-structured interviews, and they represent the space of possibilities. Amongst these videos, some represent content of tiny details whereas others contain colourful regions. These aspects were considered as representative attributes by the surgeons during the interviews.

Fig. 3.1 shows one representative frame from each of the four videos of open surgery. Fig. 3.2 illustrates one representative frame from each of the four videos of laparoscopic surgery. Table 3.3 describes the technical specifications of these videos.



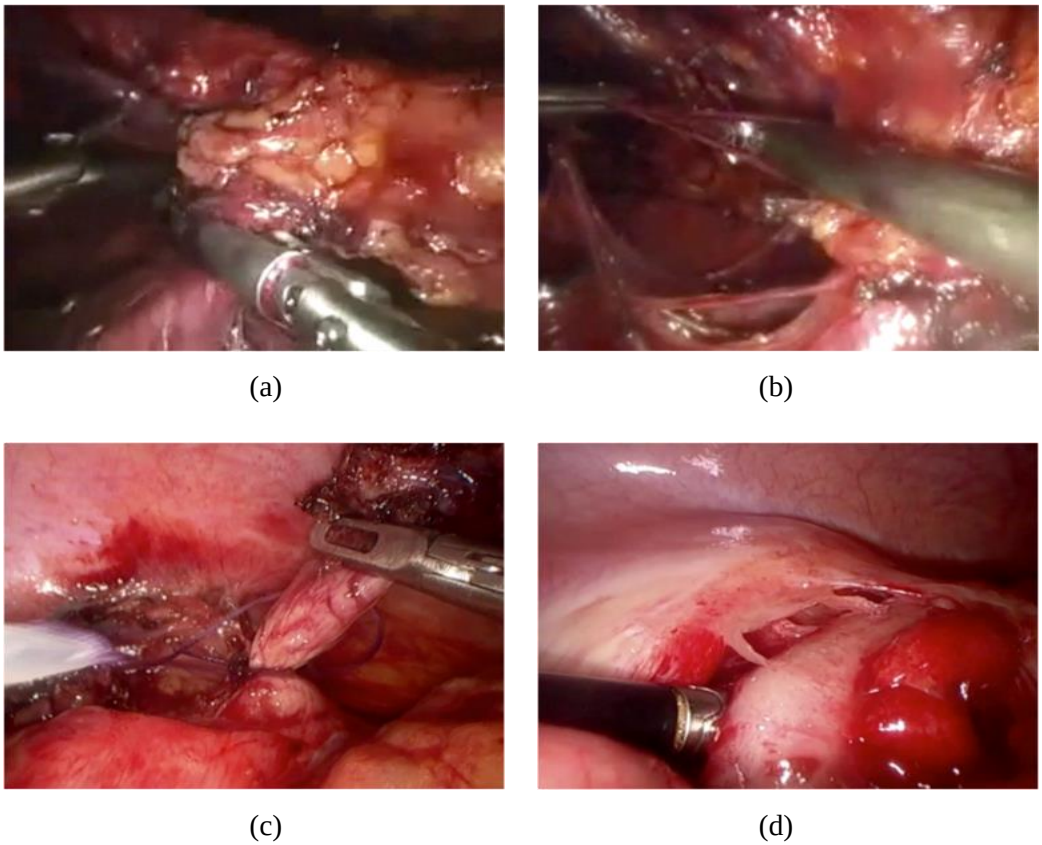
(a) (b)

(c) (d)

Fig. 3.1: Illustration of one frame from each of the four open surgery videos used in our experiment: (a) content 1 (hepatic artery dissection), (b) content 2 (small wires used to tie a knot), (c) content 3 (use of a clamp to stop a blood flow), and (d) content 4 (important bleeding during the procedure).

Table 3.3: Technical characteristics of the videos used in our experiment.

Procedure	Content	Resolution	Frame rate
Open surgery	1	872×480	30 fps
	2	872×480	30 fps
	3	960×720	30 fps
	4	960×720	30 fps
Laparoscopy	1	352×288	25 fps
	2	352×288	25 fps
	3	720×576	25 fps
	4	720×576	25 fps



(a) (b)

(c) (d)

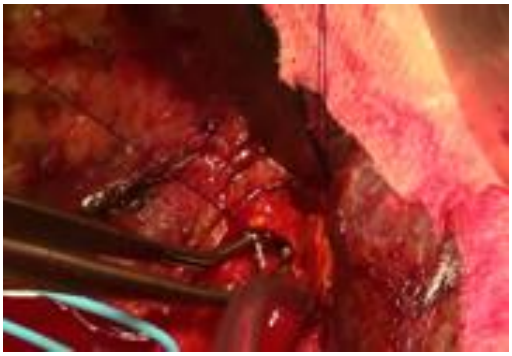
Fig. 3.2: Illustration of one frame from each of the four laparoscopic surgery videos used in our experiment: (a) content 1 (dissection of the mesenteric artery), (b) content 2 (before the artery dissection), (c) content 3 (use of an Endoloop ligature to suture), and (d) content 4 (different textures during the procedure).

To simulate a realistic telesurgery scenario, e.g., in satellite communication, various levels of compression artifacts and transmission errors were generated on the source videos. We used H.264 [27] to compress videos. H.264 is the most widely used video codec in current digital imaging systems, which allows an efficient compression of visual signals due to its advanced functionalities in temporal and spatial predictions. Videos that are compressed by H.264 typically exhibit artifacts such as blocking, blur, ringing and motion compensation mismatches. The transmission errors were simulated using packet loss generated by an internal tool (i.e., based on a Gilbert-Elliott model [92], a simple channel model chosen to study packet losses produced from wireless fading channels). We also varied the frame rate of the videos. This yielded thirty-two distorted videos for each surgical procedure, i.e., open and laparoscopic surgeries. Table 3.4 details the configuration of the dataset. Fig. 3.3 shows an example of how the video content is distorted in open surgery.

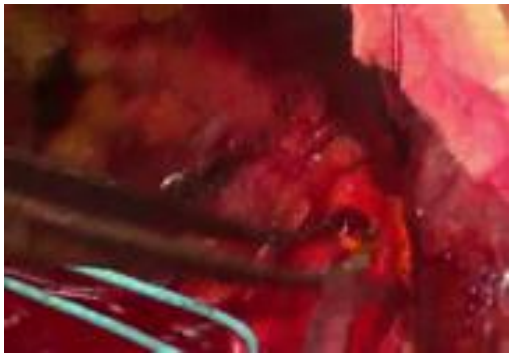
Table 3.4: Distortion parameters used in our experiment.

Procedure	Condition	Bit rate (H.264)	Frame rate	Packet loss rate
Open surgery	1	128 kbps	30 fps	0%
	2	256 kbps	30 fps	0%
	3	350 kbps	30 fps	0%
	4	512 kbps	30 fps	0%
	5	1 Mbps	30 fps	0%
	6	1 Mbps	15 fps	0%
	7	1 Mbps	30 fps	1%
	8	1 Mbps	30 fps	3%
Laparoscopy	1	128 kbps	25 fps	0%
	2	256 kbps	25 fps	0%
	3	350 kbps	25 fps	0%
	4	512 kbps	25 fps	0%
	5	1 Mbps	25 fps	0%
	6	1 Mbps	12.5 fps	0%
	7	1 Mbps	25 fps	1%
	8	1 Mbps	25 fps	3%

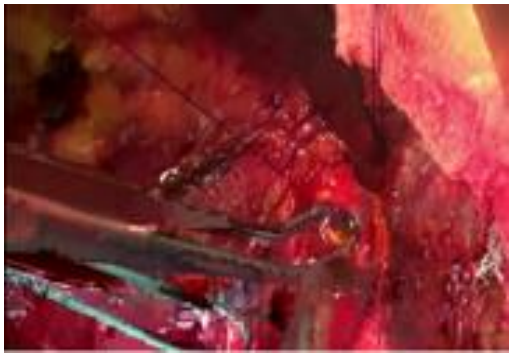
We conducted a visual perception experiment using a single-stimulus method [22], where human subjects were requested to score video quality aspects for each stimulus in the absence of a reference. The questionnaire is illustrated in Fig. 3.4, which reflects the elements extracted from the semi-structured interviews. For each video, the participants were asked to express their opinions on the general quality of the video with a task of helping a remote surgeon in mind (i.e., with an embedded view to assess the usability), using a discrete rating scale from 0 for “bad” to 10 for “excellent”. They were also asked to assess other relevant aspects of the videos, i.e., colour perception, details/edges of visual content, degree of relief and textures of objects. These application-specific attributes were identified in our qualitative study in section 3.2.



(a)



(c)



(d)

Fig. 3.3: Illustration of different types of distortions for the same content (i.e., open surgery, content 2): (a) reference (un-distorted video, 30 fps) (b) bit rate distortion (128 kbps, 30 fps), and (c) packet loss distortion (1 Mbps, 30 fps).

The experiments were conducted in a standard office environment [93] at Angers University Hospital. The stimuli were displayed on a Dell 27-inch wide-screen liquid-crystal display with a native resolution of 1920×1200 pixels. The viewing distance was approximately 60 cm. For each surgical procedure, we recruited four surgeons (note that the sample size used is considered adequate in the area of medical image perception mainly due to the high degree of consistency among medical professionals [94]) from Angers University Hospital, having from four to twenty-seven years of expertise. Before the start of the actual experiment, each participant was provided with a briefing on the goal and procedure of the experiment, including the form of the questionnaire, scoring scale, and timing. A training session was conducted in order to familiarise the participants with the distortions in videos and how to use the scale for scoring. The video stimuli used in the training were different from those used in the real experiment. After training, all test stimuli were shown one by one in a different random order to each participant in a separate session.

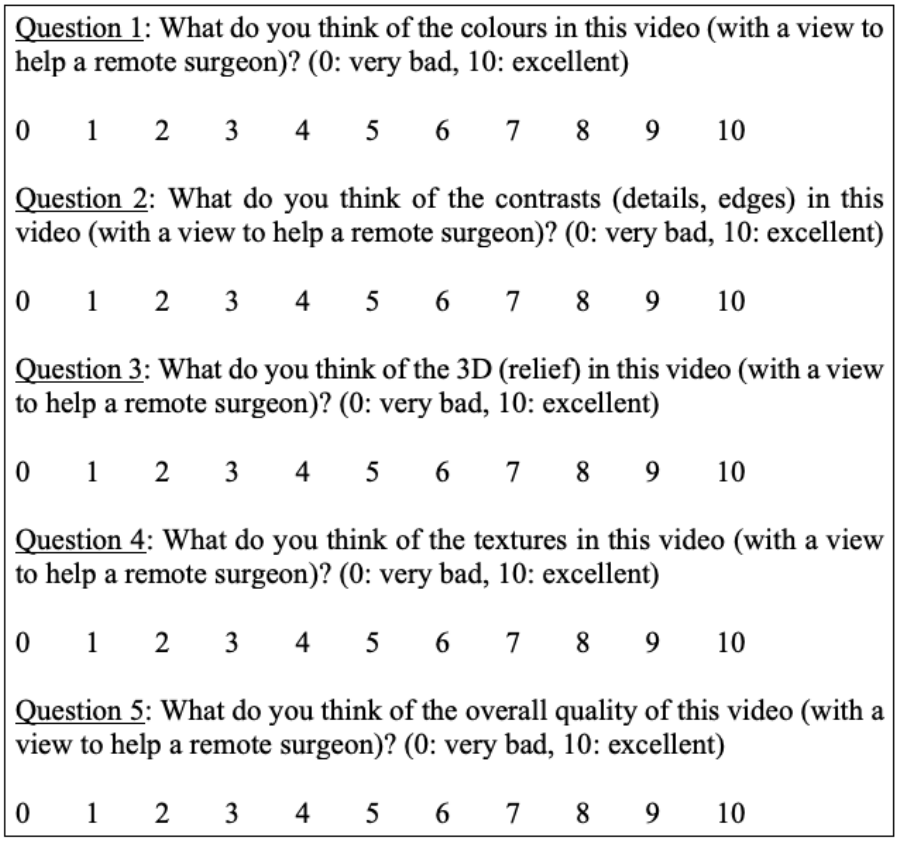


Fig. 3.4: Illustration of the questionnaire used in our experiment.

3.3.2 Results for open surgery

To process the raw data, an outlier detection and subject exclusion procedure was applied to the scores [95]-[96]. An individual score given for a video quality aspect (i.e., a particular question in Fig. 3.4) would be considered an outlier if it was outside an interval of two standard deviations around the mean score for that aspect. A subject would be rejected if more than 20% of their scores were outliers. As a result of the above procedure, none of the scores was detected as an outlier and, therefore, no surgeon was excluded from the analysis.

A correlation analysis was performed by calculating the Pearson linear correlation coefficient between the overall quality (i.e., Question 5 in Fig. 3.4) and each one of the identified video quality attributes (i.e., Question 1 to 4 in Fig. 3.4). The coefficient is 0.93 between overall quality and “colour”, and is 0.96, 0.96, and 0.97 for “contrast”, “relief” and “texture”, respectively. The results quantitatively confirm the significance of the video quality attributes identified in the qualitative study. We now focus on the statistical analysis using the overall quality scores (i.e., Question 5 in Fig. 3.4).

Fig. 3.5 illustrates the mean opinion score (MOS) averaged over all surgeons for each distorted video in our experiment. Note Fig. 3.5 is a summary of Fig. 3.6, Fig. 3.7, and Fig. 3.8 for a joint representation of the data. It shows that compression artifacts and transmission errors affect the overall quality. In addition, the effect tends to depend on the video content. The observed tendencies are further statistically analysed with an ANOVA (Analysis of Variance) using the software package SPSS version 23 (note the dependent variable is tested to be normally distributed). Based on the configuration of the stimuli as illustrated in Table 3.4, we perform three individual factorial ANOVA tests: 1) evaluation of the effect of bit rate on videos (based on conditions 1-5 in Table 3.4), 2) evaluation of the effect of frame rate on videos (based on conditions 5 and 6), and 3) evaluation of the effect of packet loss rate on videos (based on conditions 5, 7 and 8). For each case above, the video content is included in the ANOVA.

To evaluate the effect of bit rate with an ANOVA, the perceived quality is selected as the dependent variable, the video content and bit rate as fixed independent variables, and the participant as random independent variable. The two-way interactions of the fixed independent variables are included in the analysis. The results are summarised in Table 3.5, where the F-statistic (i.e., F) and its associated degrees of freedom (i.e., df) and significance (i.e., p-value) are included and show that bit rate has a significant effect on perceived quality. The post-hoc test reveals the following order in quality (note that commonly underlined entries are not significantly different from each other, based on a common 5% threshold):

128 kbps (<MOS> = 0.63) < 256 kbps (<MOS> = 3.50) < 350 kbps (<MOS> = 5.69) < <u>512 kbps (<MOS> = 7.75) < 1 Mbps (<MOS> = 8.44)</u> (also see the comparison of MOS in Fig. 3.6).

Also, the interaction between video content and bit rate is significant, which implies that the difference in quality between different bit rates is not the same for the four source videos.

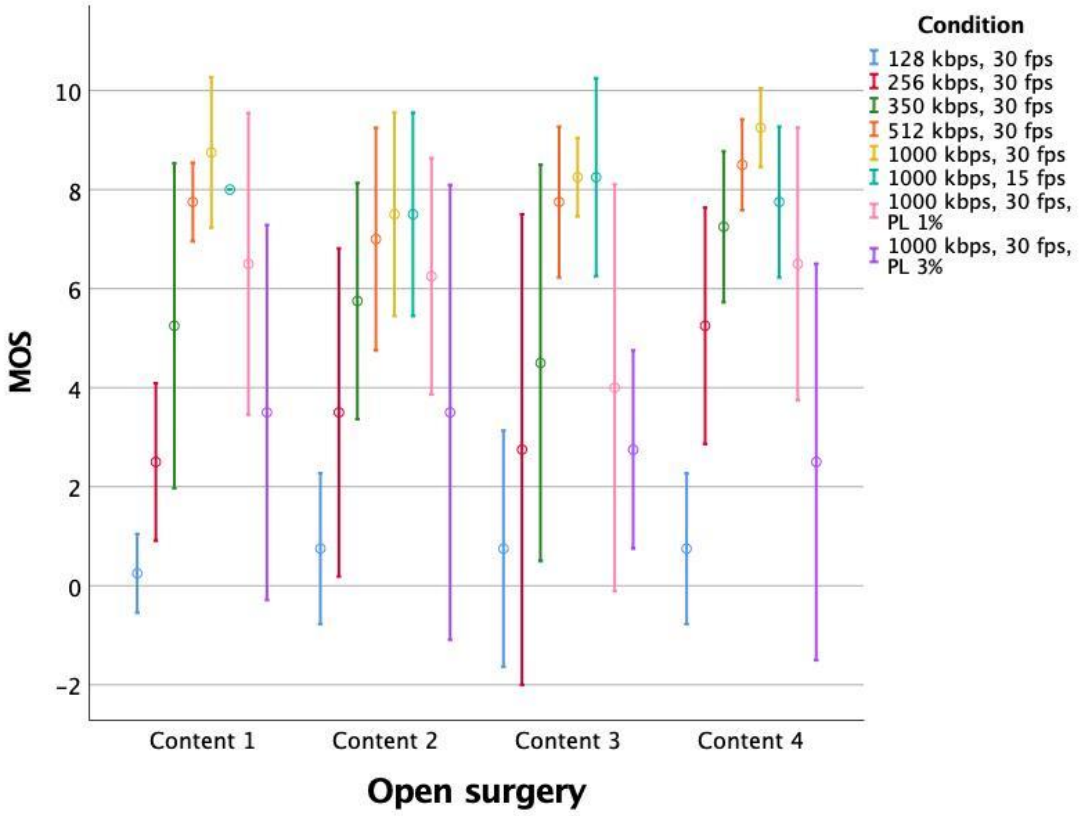


Fig. 3.5: Illustration of the mean opinion score (MOS) averaged across subjects for each distorted video for open surgery. "Content" refers to a source video. Error bars indicate a 95% confidence interval.

Table 3.5: Results of the ANOVA to evaluate the effect of "Bit rate" and "Content" on the perceived quality for open surgery.

Factor	df	F	p-value
Bit rate	4	89.445	<0.001
Content	3	3.255	0.074
Bit rate * Content	12	2.230	0.032

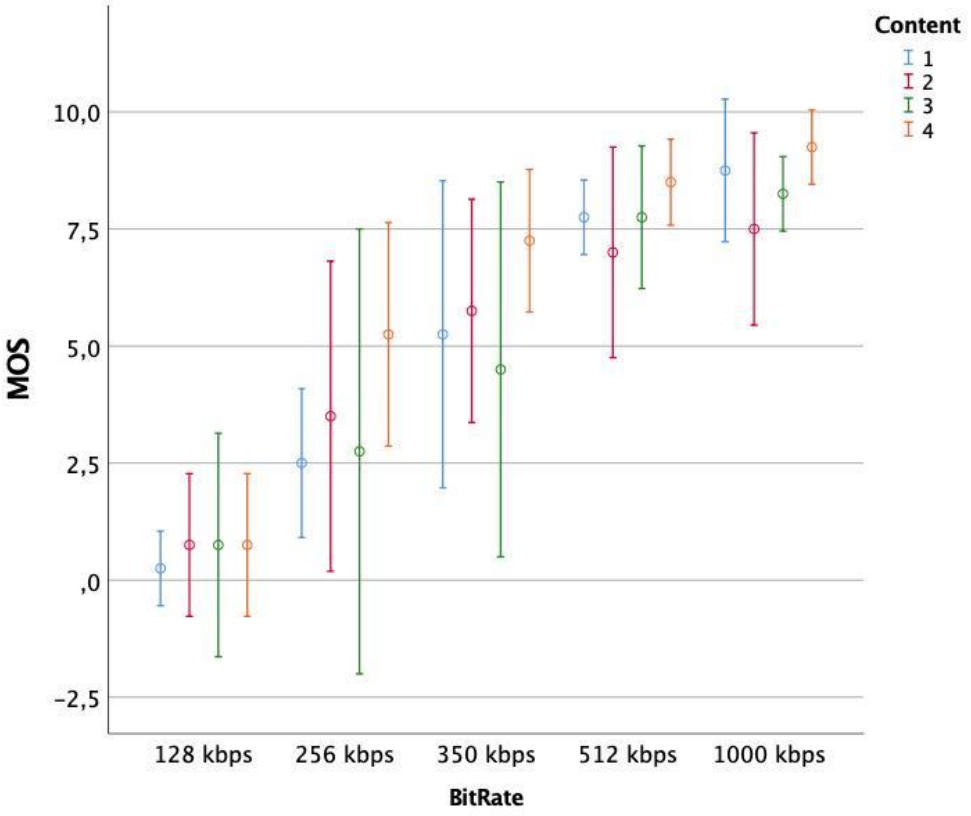


Fig. 3.6: Illustration of the effect of bit rate on open surgery videos. Error bars indicate a 95% confidence interval.

The results of the ANOVA to evaluate the effect of frame rate on videos are summarised in Table 3.6 and show that the effects are not statistically significant. The post-hoc test reveals the following order in quality (note that commonly underlined entries are not significantly different from each other):

15 fps (<MOS> = 7.88) < 30 fps (<MOS> = 8.44) (also see the comparison of MOS in Fig. 3.7).

Table 3.6: Results of the ANOVA to evaluate the effect of "Frame rate" and "Content" on the perceived quality for open surgery.

Factor	df	F	p-value
Frame rate	1	4.765	0.117
Content	3	1.809	0.216
Frame rate * Content	3	2.168	0.162

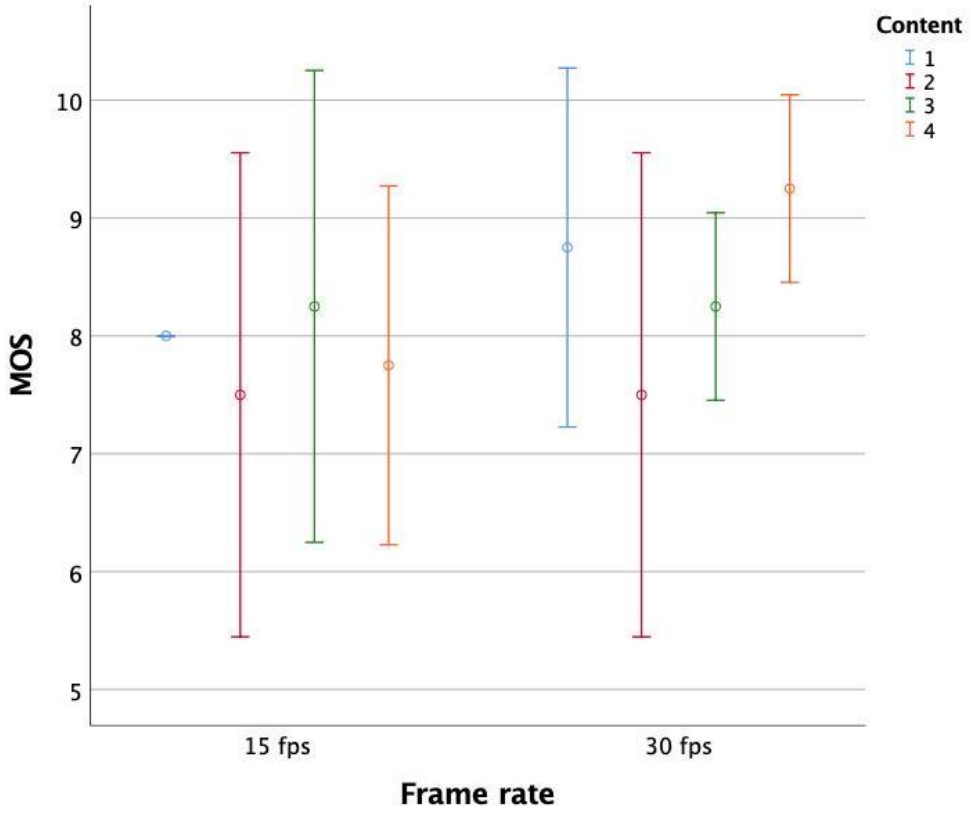


Fig. 3.7: Illustration of the effect of frame rate on open surgery videos. Error bars indicate a 95% confidence interval.

The results of the ANOVA to evaluate the effect of packet loss on videos are summarised in Table 3.7, and show that packet loss rate has a significant effect on perceived quality. The post-hoc test reveals the following order in quality:

3% (<MOS> = 3.063) < 1% (<MOS> = 5.81) < 0% (<MOS> = 8.44) (also see the comparison of MOS in Fig. 3.8).

Table 3.7: Results of the ANOVA to evaluate the effect of "Packet loss rate" and "Content" on the perceived quality for open surgery.

Factor	df	F	p-value
Packet loss rate	2	17.858	0.003
Content	3	2.673	0.082
Packet loss rate * Content	6	2.538	0.059

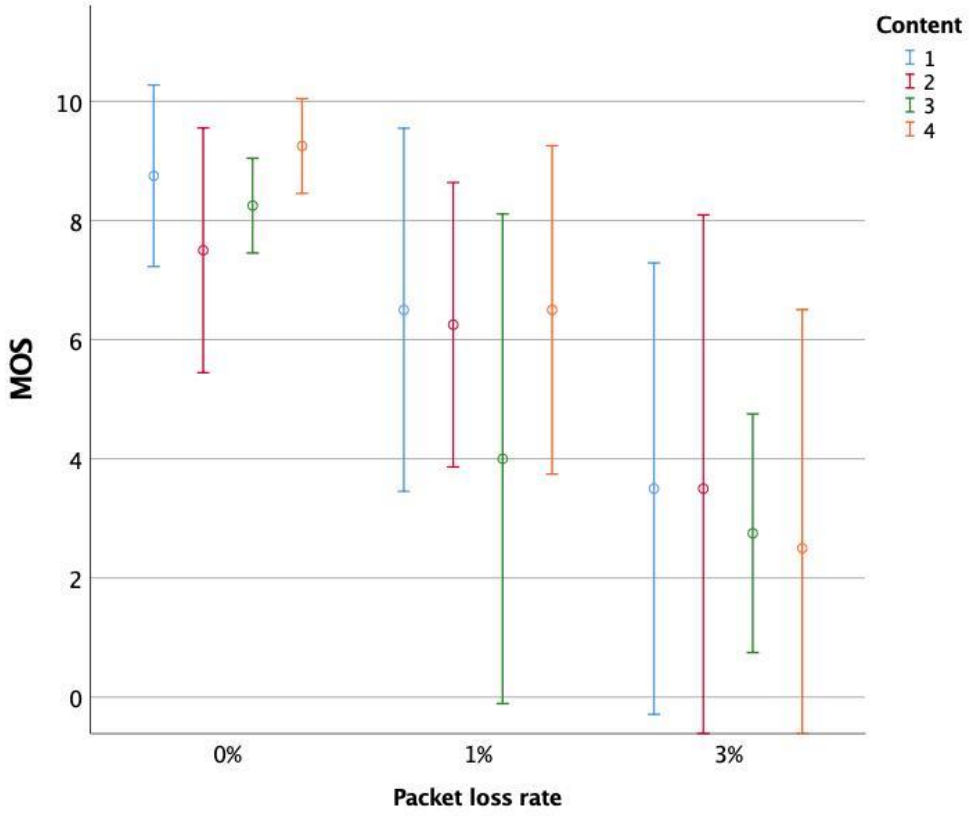


Fig. 3.8: Illustration of the effect of packet loss on open surgery videos. Error bars indicate a 95% confidence interval.

3.3.3 Results for laparoscopic surgery

We take the same statistical approach as used above to analyse the subjective data collected for laparoscopic surgery.

As a result of the outlier removal and subject exclusion procedure, none of the scores given by the surgeons was detected as an outlier, and therefore, no subject was excluded. The Pearson coefficient is 0.89 between overall quality and “colour”, and is 0.94, 0.96, and 0.96 for “contrast”, “relief” and “texture” respectively. Fig. 3.9 illustrates the mean opinion score (MOS) averaged over all surgeons for each distorted video for laparoscopic surgery.

An ANOVA was performed to evaluate the effect of bit rate on videos. The results are summarised in Table 3.8 and show that bit rate has a significant effect on perceived quality. The post-hoc test reveals the following order in quality (note that commonly underlined entries are not significantly different from each other based on a common 5% threshold):

128 kbps (<MOS> = 2.25) < 256 kbps (<MOS> = 4.5) < 350 kbps (<MOS> = 5.25) < 512 kbps (<MOS> = 7.25) < 1 Mbps (<MOS> = 8.13) (also see the comparison of MOS in Fig. 3.10).

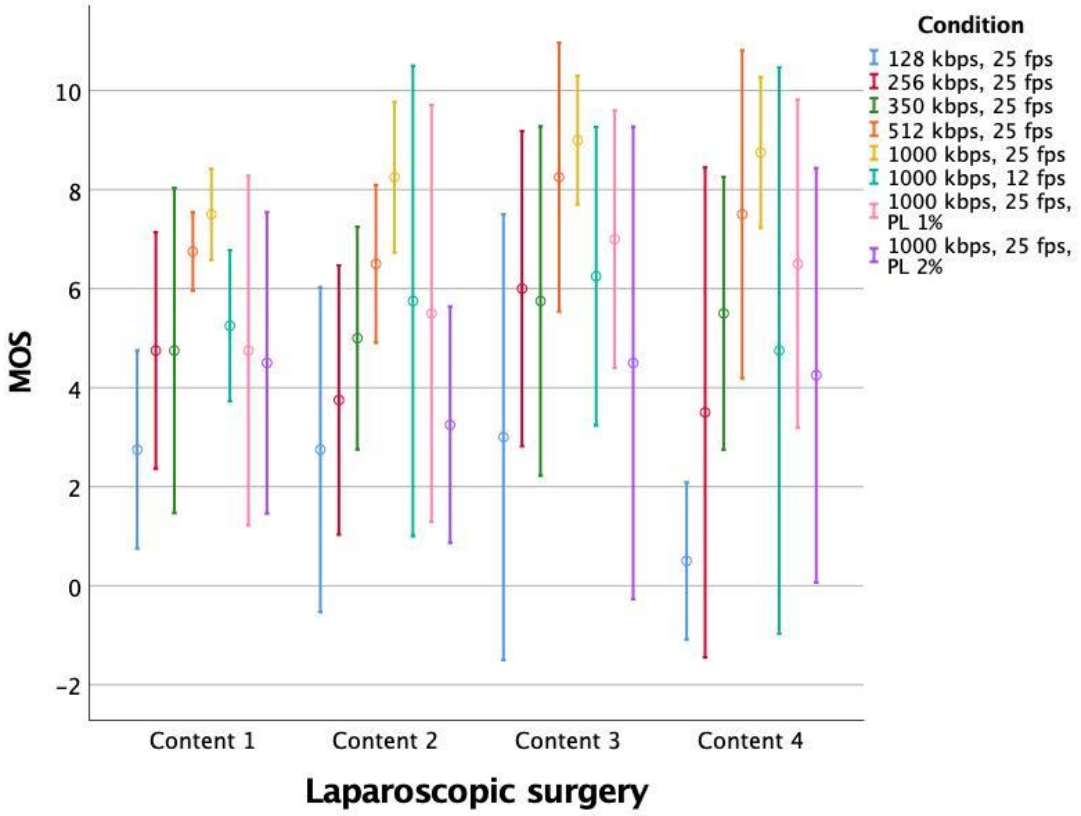


Fig. 3.9: Illustration of the mean opinion score (MOS) averaged across subjects for each distorted video for laparoscopic surgery. "Content" refers to a source video. Error bars indicate a 95% confidence interval.

Table 3.8: Results of the ANOVA to evaluate the effect of "Bit rate" and "Content" on the perceived quality for laparoscopic surgery.

Factor	df	F	p-value
Bit rate	4	63.676	<0.001
Content	3	3.395	0.067
Bit rate * Content	12	1.970	0.058

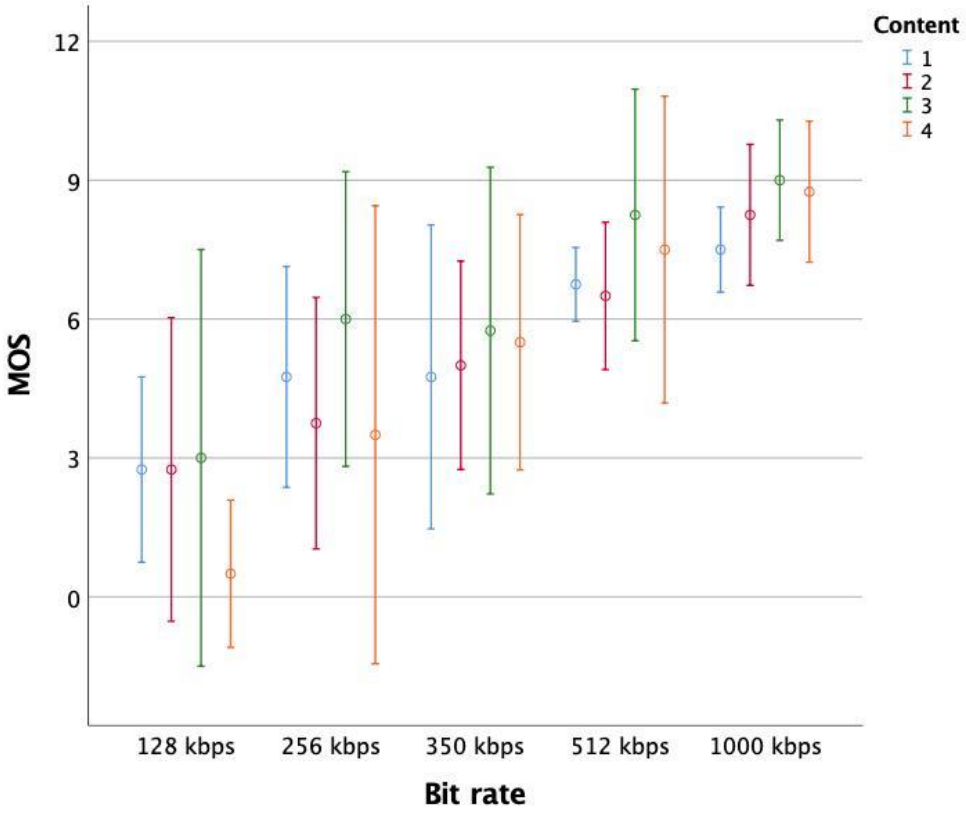


Fig. 3.10: Illustration of the effect of bit rate on laparoscopic surgery videos. Error bars indicate a 95% confidence interval.

The results of the ANOVA to evaluate the effect of frame rate on videos are summarised in Table 3.9 and show that the effects are statistically different. The post-hoc test reveals the following order in quality:

12.5 fps (<MOS> = 5.50) < 25 fps (<MOS> = 8.13) (also see the comparison of MOS in Fig. 3.11).

Table 3.9: Results of the ANOVA to evaluate the effect of "Frame rate" and "Content" on the perceived quality for laparoscopic surgery.

Factor	df	F	p-value
Frame rate	1	10.099	0.050
Content	3	1.538	0.271
Frame rate * Content	3	1.112	0.394

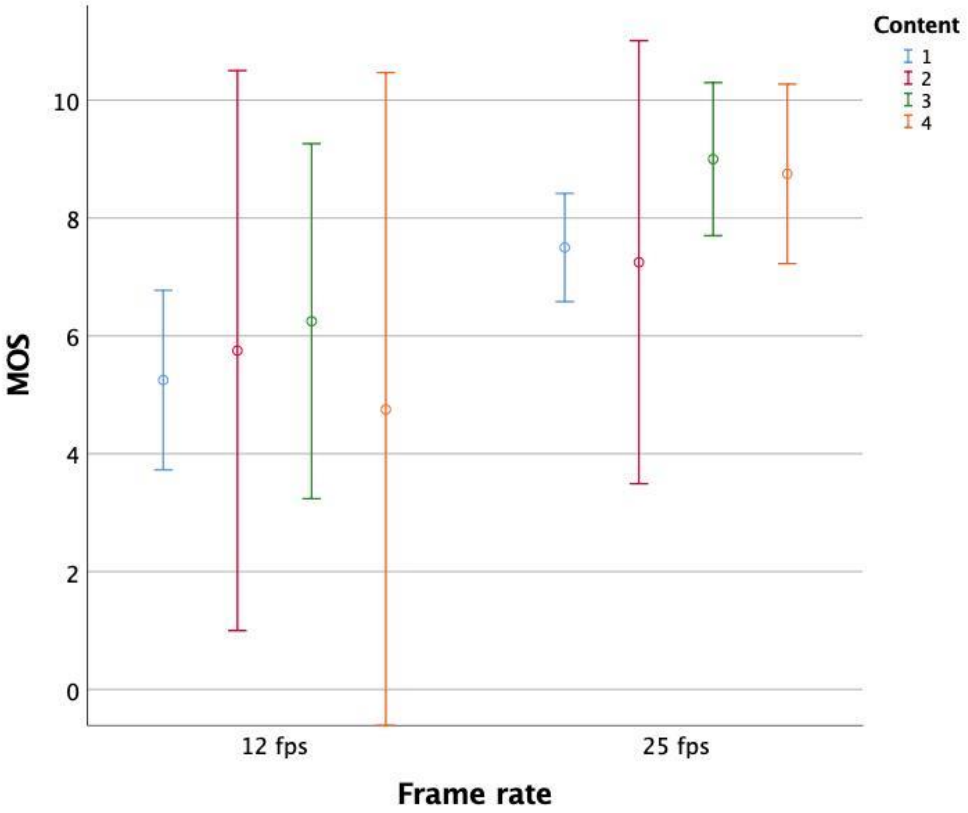


Fig. 3.11: Illustration of the effect of frame rate on laparoscopic surgery videos. Error bars indicate a 95% confidence interval.

The results of the ANOVA to evaluate the effect of packet loss rate on videos are summarised in Table 3.10 and show that packet loss has a significant effect on perceived quality. The post-hoc test reveals the following order in quality:

3% (<MOS> = 4.13) < 1% (<MOS> = 5.88) < 0% (<MOS> = 8.13) (also see the comparison of MOS in Fig. 3.12).

Table 3.10: Results of the ANOVA to evaluate the effect of "Packet loss rate" and "Content" on the perceived quality for laparoscopic surgery.

Factor	df	F	p-value
Packet loss rate	2	15.029	0.005
Content	3	6.187	0.094
Packet loss rate * Content	6	0.795	0.586

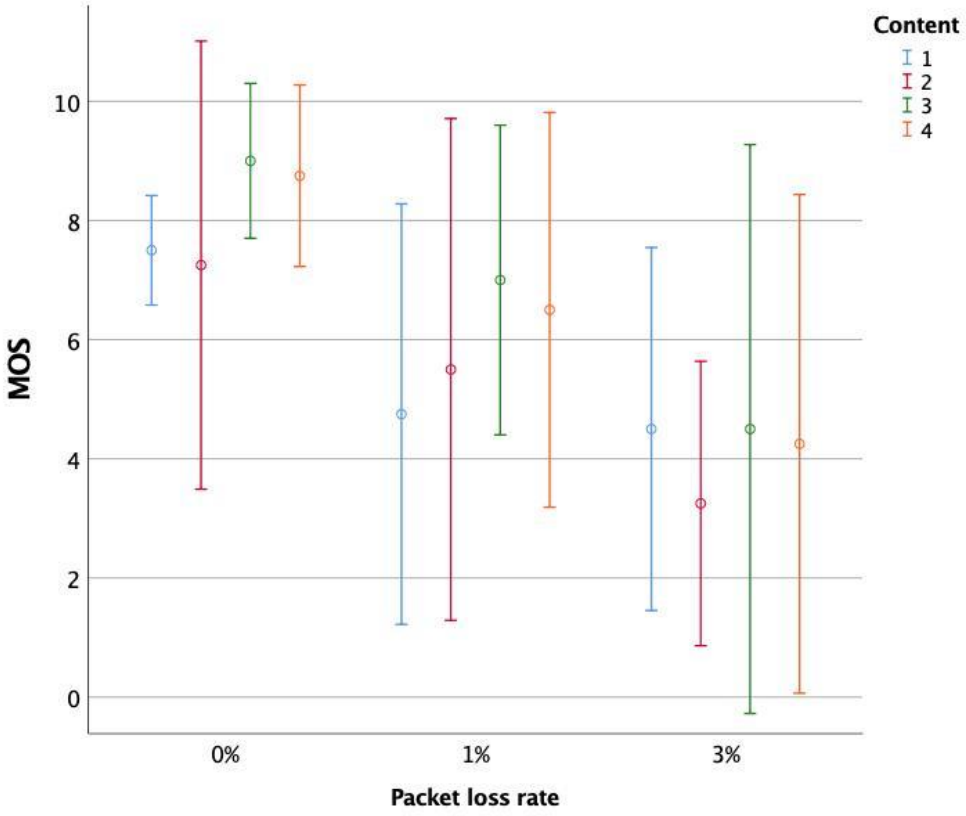


Fig. 3.12: Illustration of the effect of packet loss on laparoscopic surgery videos. Error bars indicate a 95% confidence interval.

3.4 Dedicated study: the impact of video compression

3.4.1 Methodology

For this experiment, we re-used the four open surgery original videos presented in Fig. 3.1. This time, the source videos were compressed using two compression schemes: H.264 [27] and HEVC [30]. HEVC has recently been introduced and will presumably soon be established as state of the art. HEVC compressed videos often exhibit mosquito noise around large regions of moving content. For each source video, seven compressed videos were created: 256, 384 and 512 kbps using H.264 and 128, 256, 384 and 512 kbps using HEVC. This resulted in a test database of 32 video stimuli, including the originals.

Since standardised methodology for the subjective assessment of the quality of medical images/videos does not exist, we decided to make use of the methodology established for natural images/videos and modify it to telesurgery content. These methodologies are already described in detail in Chapter 2, where various experiment protocols are

prescribed in order to suit different needs and environments of subjective visual testing while achieving consistent outcomes. The differences between diverse protocols include whether the reference (distortion free) stimulus is presented to participants when assessing the quality of the test (distorted) stimulus, and whether an absolute category rating scale or a continuous rating scale is used for scoring quality, etc. In making these choices and deciding on an appropriate protocol, factors that are often considered and traded off in practice include the ease of rating, timescale and reliability of data collection. Based on preliminary tests and on a survey of surgeons' preference for scoring methodology, we adopted the concept of SAMVIQ (Subjective Assessment Methodology for Video Quality), where video sequences are shown in multi-stimulus form, so that the subject can choose the order of tests and correct their votes as appropriate [97]. With SAMVIQ, in contrast to the conventional methodologies prescribed in [21], subjects can directly compare the impaired sequences among themselves and against the reference.

The final scoring interface developed in our study is illustrated in Fig. 3.13, where the subjects are asked to assess the overall quality of each video by inserting a slider mark on a vertical scale. The grading scale is continuous (with the score range [0, 100]) and is divided into three semantic portions for the purpose of scoring surgical videos. The associated terms categorising the different levels are: "Not annoying" (i.e., [75, 100]) corresponding to "the quality of the video enables you to efficiently communicate with a remote colleague without perceiving any visual artifact"; "Annoying but acceptable" (i.e., [25, 75]) referring to "the visual artifacts are noticeable but the quality of the video suffices for the conduct of telesurgery"; and "Not acceptable" (i.e., [0, 25]) meaning "the visual artifacts are very noticeable and interfere with the telesurgery practice". Fig. 3.13 also shows an example of the test organisation for each scene, where an explicit reference (i.e., noted to the subjects), a hidden reference (i.e., a freestanding stimulus among other stimuli), and seven compressed videos (placed in a different random order to each participant) are included. Quality scoring is carried out scene after scene; from one scene to the next, the sequences are randomised. Within a test (per scene), subjects are allowed to view and grade any stimulus in any order, and each stimulus can be viewed and assessed as many times as the subject wishes (note the last grade remains recorded). The entire methodology was developed in consultation with expert surgeons to make sure the scoring experiment is more relevant to the real clinical practice.

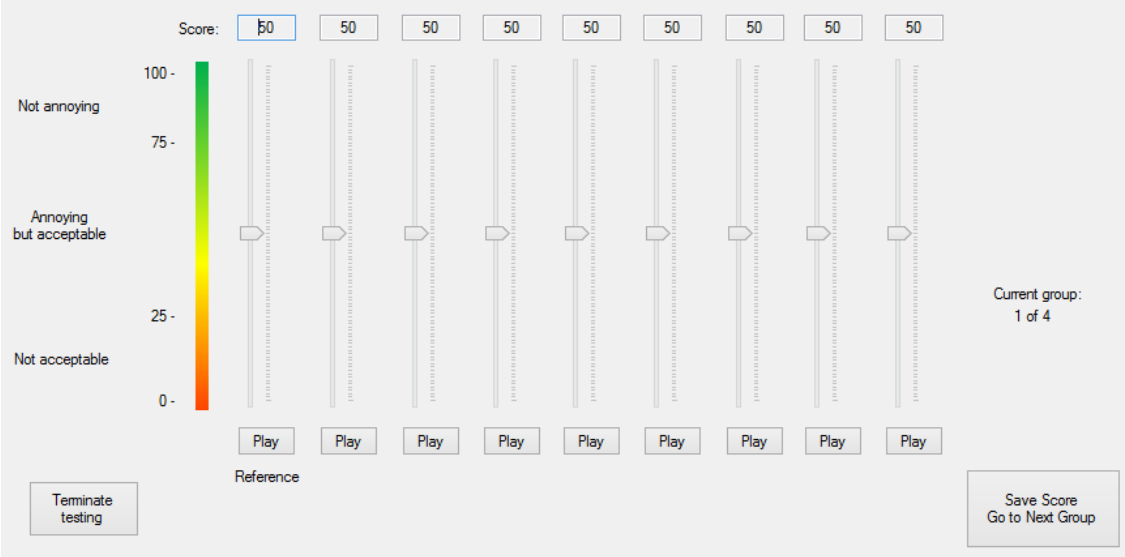


Fig. 3.13: Illustration of the rating interface used in our experiment.

We set up a standard office environment [93] at Angers University Hospital for the conduct of the experiment. The venue represented a controlled viewing environment to ensure consistent experimental conditions: low surface reflectance and approximately constant ambient light. For the display of the test stimuli, we used a Dell 27-inch wide-screen liquid-crystal display with a native resolution of 1920×1200 pixels. No video adjustment (zoom, window level) was allowed during the experiment.

Eight abdominal surgeons (having three to twenty-seven years of experience in surgery) from Angers University Hospital participated in the experiment. Note the surgeons who participated in the preliminary study did not participate in the dedicated study. Each participant was first given written instructions on the experimental procedure prior to the start of the actual testing. A training session was then performed where participants had the opportunity to understand the specific visual distortions and to familiarise themselves with how to use the range of the scoring scale. As for the preliminary study, the stimuli shown in the training session were different from those presented in the actual experiment.

3.4.2 Experimental results

After the subjective experiment, raw scores were filtered to reject outlier evaluations and individuals, as already explained in Section 3.3.2. This procedure caused only two scores to be rejected as outliers (i.e., one for “Content 1” and one for “Content 4”), and no surgeon to be rejected. After data filtering, the remaining scores were analysed.

Fig. 3.14 gives the mean opinion score (MOS) averaged over all participants, for each compressed surgical video in our subjective experiment. It clearly illustrates that the compression scheme (i.e., H.264 versus HEVC) and the compression ratio impact the perceived video quality. The figure also shows that the change of quality tends to depend on the content of the stimulus. To statistically analyse the observed tendencies, we performed a full factorial ANOVA using the subjective quality as the dependent variable, the video content and compression (i.e., scheme and ratio) as fixed independent variables, and the participant as random independent variable (note the dependent variable is tested to be normally distributed). The statistical analysis also contained the two-way interactions of the fixed variables. Table 3.11 summarises the results, including for each variable the F-statistic (F-value), the degrees of freedom (df) and the significance (p-value). These results indicate that all main effects and interactions are statistically significant. Not all source videos (i.e., “Content”) receive the same average rating of quality (note underlined items are not statistically different from each other):

“Content 4” < “Content 2” < <u>“Content 3” < “Content 1”</u>

There is also a significant difference in quality between the seven configurations of compression, and the statistical analysis reveals the following order of average quality:

<u>HEVC: 128 kbps < H.264: 256 kbps</u> < <u>H.264: 384 kbps < HEVC: 256 kbps</u> < H.264: 512 kbps < <u>HEVC: 384 kbps < HEVC: 512 kbps</u>

In addition, the interaction between content and compression is significant. This indicates that the impact the different compression strategies have on quality depends on the video content.

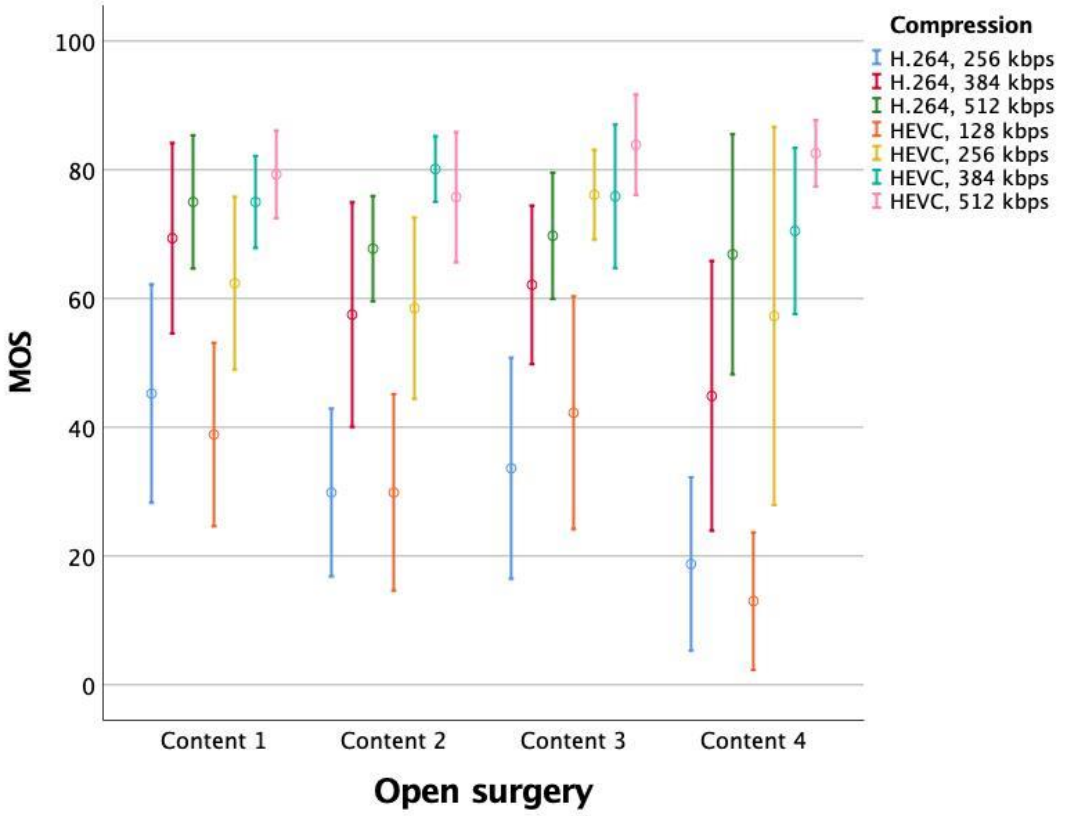


Fig. 3.14: Illustration of the mean opinion score (MOS) averaged over all subjects for each compression video. "Content" refers to a source video. Error bars indicate a 95% confidence interval.

Table 3.11: Results of the ANOVA to evaluate the effects of "Participant", "Content" and "Compression" on the perceived quality.

	df	F	p-value
Participant	7	3.869	0.004
Content	3	4.751	0.011
Compression	6	42.047	<0.001
Content * Compression	18	2.386	0.003

Fig. 3.15 illustrates the impact of the compression strategy on the perceived quality. It can be seen that, for each compression scheme (i.e., either H.264 or HEVC), the perceived quality monotonically increases with the increase of bit rate. At low quality, one can conclude that the bit rate of H.264 (i.e., H.264: 256 kbps) should be two times as high as the bit rate of HEVC (i.e., HEVC: 128 kbps) to be perceived as equal quality.

At higher bit rate, to achieve the same perceived quality, the bit rate of H.264 (i.e., H.264: 384 kbps) should be 1.5 times the bit rate of HEVC (i.e., HEVC: 256 kbps). Pairwise comparisons are further performed with hypothesis testing between the two compression schemes. The results are summarised in Table 3.12, where a paired sample *t*-test is performed if both samples are normally distributed; otherwise, in the case of non-normality, a nonparametric version analogue to a paired sample *t*-test (i.e., Wilcoxon signed rank sum) is conducted. It clearly indicates that there is no statistically significant difference between H.264: 256 kbps and HEVC: 128 kbps, and that similarly for the following pairwise comparisons: H.264:384 kbps vs. HEVC: 256 kbps, and HEVC: 384 kbps vs. HEVC: 512 kbps, the difference is not statistically significant for each case.

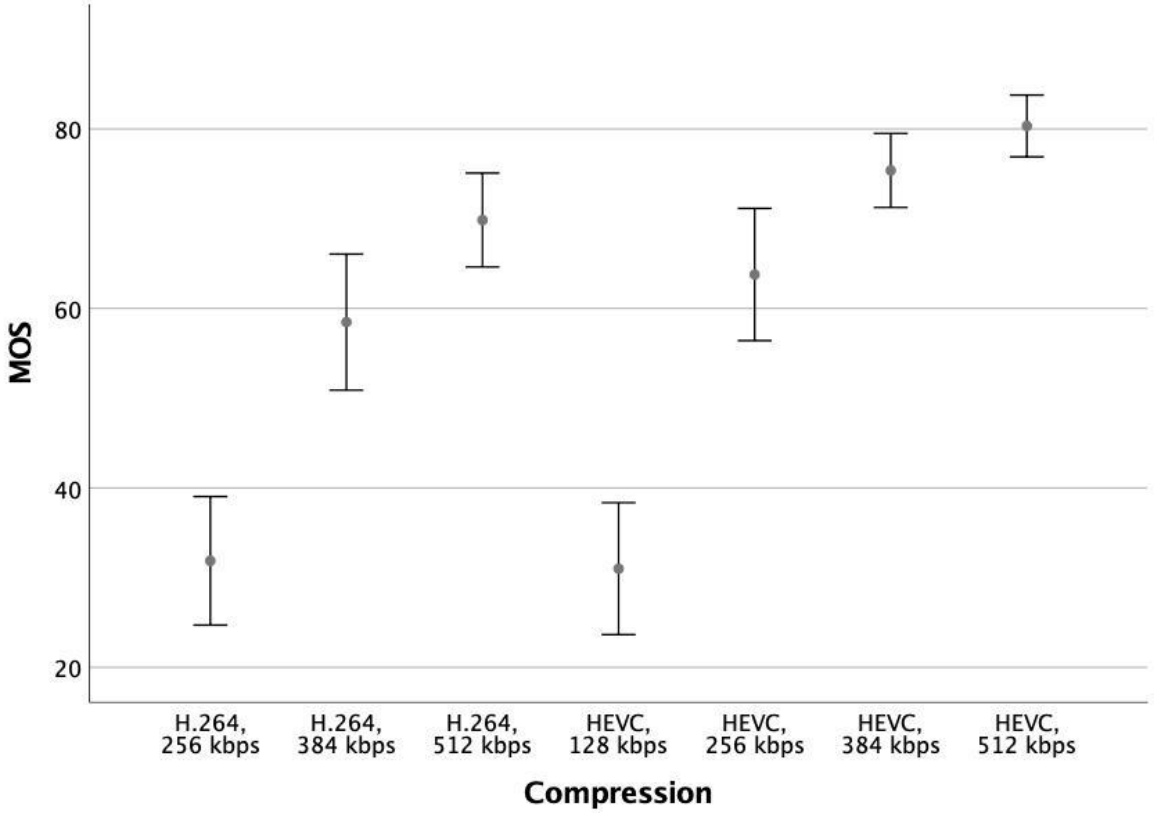


Fig. 3.15: Illustration of quality averaged over all subjects and all source videos for each compression configuration. Error bars indicate a 95% confidence interval.

Table 3.12: Results of the statistical significance for pairwise comparisons. Each entry in the table represents a code word consisting of one out of three symbols: "1" means that the configuration for the row is statistically better than the configuration for the column, "0" means that it is statistically worse, and "-" means that it is statistically indistinguishable.

	H:264, 256 kbps	H.264: 384 kbps	H.264: 512 kbps	HEVC: 128 kbps	HEVC: 256 kbps	HEVC: 384 kbps	HEVC: 512 kbps
H.264: 256 kbps		0	0	-	0	0	0
H.264: 384 kbps	1		0	1	-	0	0
H.264: 512 kbps	1	1		1	1	0	0
HEVC: 128 kbps	-	0	0		0	0	0
HEVC: 256 kbps	1	-	0	1		0	0
HEVC: 384 kbps	1	1	1	1	1		-
HEVC: 512 kbps	1	1	1	1	1	-	

3.5 Main findings and contributions

We conducted subjective experiments to study how variations in video distortion can affect the quality perception of surgeons in the practice of telesurgery, with two distinct procedures, i.e., open surgery and laparoscopic surgery.

For both procedures, compression artifacts have a statistically significant effect on the perceived quality. More specifically, for open surgery, H.264 compression has a significant impact on the quality, and the way video quality changes with the bit rate depends on the video content. The impact of video content is probably due to that content itself may induce an intrinsic difference in sensitivity to distortion and thus, in the annoyance of distortion. However, the results showed that there is no statistically significant difference between the two higher bit rates studied, i.e., 512 kbps and 1 Mbps. For laparoscopic surgery, the impact of the different bit rates on video quality is the same for all video scenes. No statistically significant difference was found between intermediate bit rates, i.e., 256 kbps and 350 kbps with H.2.64.

We also found that at high bit rate (i.e., 1 Mbps), transmission errors (i.e., packet loss) can significantly reduce the perceived video quality for both surgical procedures in the similar way. The quality of videos for open surgery is not sensitive to the change of frame rate (i.e., from 30 to 15 frames per second). For laparoscopic surgery, videos with a lower frame rate are scored lower in quality than videos with a higher frame rate (i.e., from 25 to 12.5 frames per second).

A dedicated study to assess the impact of the compression strategy for open surgery was also designed and conducted. The results showed that the bit rate of H.264 compressed videos has to be two times the bit rate of HEVC compressed videos to provide the same perceived quality in telesurgery at low quality (i.e., H.264: 256 kbps) and 1.5 times the bit rate of HEVC compressed videos at higher quality (i.e., H.264: 384 kbps).

Chapter 4:
The impact of medical specialty on the perceived quality

4.1 Introduction

As introduced previously, the perception of medical image quality is critical to clinical practice. In the previous chapter, we presented a study on how medical professionals perceive medical imaging. However, since health professionals are increasingly viewing medical images in a variety of environments, it is important to understand quality perception across speciality practice settings. Little progress has been made towards this purpose. In radiology practice, there are two groups of professionals who interact with and process image information. A radiologist is a doctor who is specially trained to interpret diagnostic images, and a radiographer is a person who has been trained to acquire medical images (note if a radiographer has been trained to perform an ultrasound, he/she may be called a sonographer). Both specialities are important for medical diagnosis. However, very little is known about the difference between radiologists and radiographers in term of their perception of image quality.

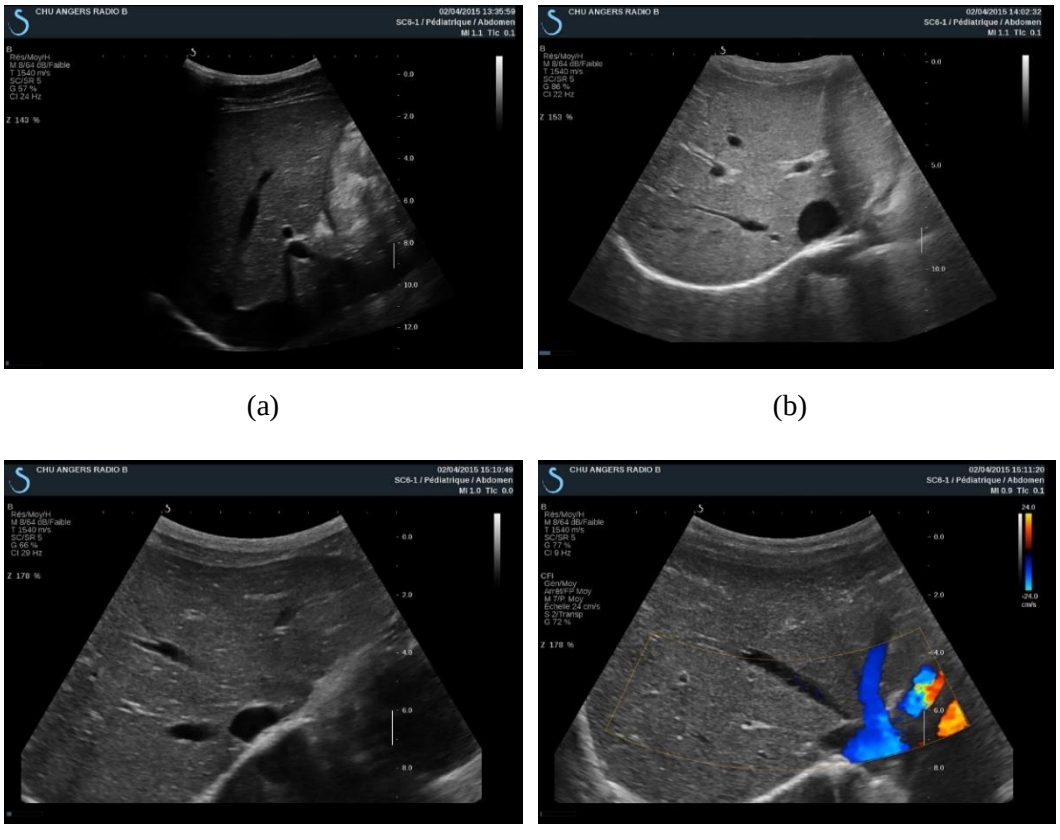
In this chapter, we investigate whether and to what extent specialty practice, i.e., radiologists versus sonographers, affect the quality perception of ultrasound video, through perception experimentation with compressed visual stimuli.

4.2 Visual quality perception experiment with radiologists and sonographers

4.2.1 Stimuli

Unlike other related visual quality assessment studies in the literature which are either limited to a specific compression scheme or a small degree of stimulus variability, we aim to study a more comprehensive set of stimuli of a larger diversity in visual content and distortion. By this, we mean the dataset would include alternative popular

compression schemes and various source stimuli and degradation levels. In the meantime, we seek to limit the total number of stimuli in order to make the subjective testing realistic so that the results are reliable. The source videos used in our experiments were extracted from four distinctive hepatic ultrasound scans by a senior radiologist from Angers University Hospital in France. To avoid potential bias, the radiologist was not involved in the later stages of the experiments. It should be noted that, although the videos were from patients, they were purposely selected so that there was no apparent pathology. Also, the participants were not informed of the indications for the scans. The reason behind above choices is to encourage the participants to consider all plausible clinical uses of the stimuli rather than focusing on a specific pathology. All source videos last twelve seconds each and have a resolution of 1920×1080 pixels at a frame rate of 25 frames per second (fps). Fig. 4.1 illustrates one representative frame of each source video.



(a) (b)

(c) (d)

Fig. 4.1: Illustration of one frame from each of the four source videos used in our experiment: (a) Content 1, (b) Content 2, (c) Content 3, and (d) Content 4 (in contrast to Content 1-3, Content 4 includes a Doppler ultrasound used to follow the blood flows).

The source videos were compressed using two popular compression schemes, already described in Chapter 3: H.264 [27] and HEVC [30]. HEVC, the successor of H.264, is meant to provide a better perceptual quality than H.264 at the same bit rate [98]. Both compression schemes could be potentially applied to the compression of clinical ultrasound video. To vary the perceptual video quality, seven compressed sequences were created for each source video using the following bit rates: 512, 1000 and 1500 kbps (kilobits per second) for H.264 and 384, 512, 768 and 1000 kbps for HEVC. This resulted in a database of 32 video stimuli including the originals (i.e., 4 source videos + 4×7 compressed videos). It is well known that bit rate is not equal to quality for natural scenes, and that using the same bit rate to encode different natural contents could result in dramatically different visual quality. However, studies on to what extent the quality perception of medical content is dependent on the specific user group are largely unexplored. The knowledge would be useful for the delivery of more usable visual content that is optimally rendered for the best performance and experience of clinical professionals.

4.2.2 Experimental procedure

To make our experiment feasible for radiologists, we conducted a user study where a few medical experts were surveyed for their preference in scoring quality of ultrasound videos. Based on the results of the survey, we decided to adopt a similar concept proposed by an established methodology, SAMVIQ [97], as already described in Chapter 3.

Fig. 4.2 illustrates the final scoring interface developed in our study. In the experiment, the subjects are asked to assess the overall quality of each video by inserting a slider mark on a vertical scale. The grading scale is continuous (with the score range [0, 100]) and is divided into three semantic portions to help clinical experts in placing their opinions on the numerical scale. The associated terms categorising the different portions are: “Not annoying” (i.e., [75, 100]) corresponding to “the quality of the video enables you to conduct clinical practice without perceiving any visual artifacts”; “Annoying but acceptable” (i.e., [25, 75]) referring to “the visual artifacts are noticeable but the quality of the video suffices for the conduct of clinical practice”; and “Not acceptable” (i.e., [0, 25]) meaning “the visual artifacts are very noticeable and interfere with the clinical practice”. Fig. 4.2 also shows an example of the test

organisation for each source scene, where an explicit reference (i.e., noted to the subjects), a hidden reference (i.e., a freestanding stimulus among other test stimuli) and seven compressed versions (placed in a different random order to each participant) are included. For each participant, the experiment is carried out scene after scene; and the order of scenes is randomised. Within a test (per scene), as shown in Fig. 4.2, subjects are allowed to view and grade any stimulus in any order; and each stimulus can be viewed and assessed as many times as the subject wishes (note the last score remains recorded). Note the entire methodology was developed in consultation with clinical experts to make sure the scoring experiment is more relevant and realistic to the reading environments in real clinical practice.

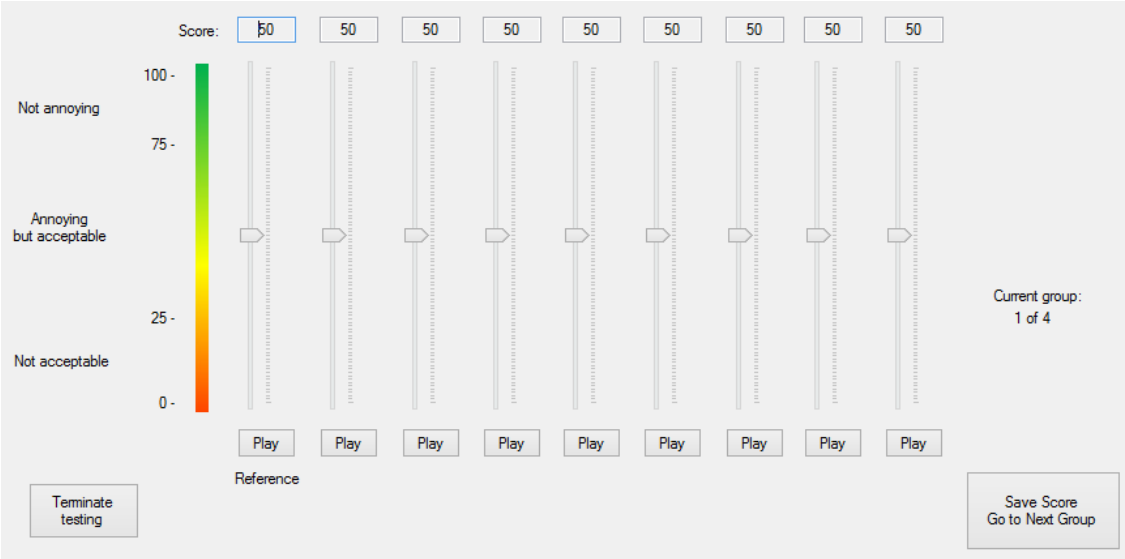


Fig. 4.2: Illustration of the rating interface used in our experiment.

4.2.3 Test environment and participants

The experiment was conducted in a typical radiology reading room environment. The venue represented a controlled viewing environment to ensure consistent experimental conditions: low surface reflectance and approximately constant ambient light (i.e., with an indirect horizontal illumination of 100 lux). The stimuli were displayed on a Dell UltraSharp 27-inch wide-screen liquid-crystal display with a native resolution of 2560×1440 pixels, which was calibrated to the Digital Imaging and Communications in Medicine (DICOM): Grayscale Standard Display Function (GSDF) [99]-[101]. The

viewing distance was approximately 60 cm. No video adjustment (zoom, window level) was allowed.

Before the start of the actual experiment, each participant was provided with instructions on the procedure of the experiment (e.g., explaining the type of assessment and the scoring interface). A training session was conducted in order to familiarise the participants with the visual distortions involved and with how to use the range of the scoring scale. The video stimuli used in the training were different from those used in the real experiment. After training, all test stimuli were shown to each participant.

Since the goal of the study is to investigate visual quality perception across different specialities, our experiments were conducted with both radiologists and sonographers. Eight radiologists were recruited from Angers University Hospital, Angers, France, and nine sonographers from Castle Hill Hospital and Hull Royal Infirmary, Hull, United Kingdom.

4.3 Image quality assessment behaviour analysis: radiologists versus sonographers

The two sets of raw data, one collected from radiologists and one from sonographers, were individually processed in the same way. Firstly, a simple outlier detection and subject exclusion procedure, as previously described in Chapter 3, was applied to the raw scores within a subject group [95]-[96]. As a result of the outlier removal and subject exclusion procedure, none of the scores were detected as an outlier in both datasets and, therefore, no radiologists or sonographers were excluded from further analysis.

Fig. 4.3 and Fig. 4.4 illustrate the mean opinion score (MOS), averaged over all subjects (within a subject group) for radiologists and sonographers, respectively, for each compressed video in our experiment. It can be seen clearly from these figures that sonographers appear to be more bothered by the low-quality videos than radiologists, as sonographers scored the highly compressed videos (i.e., H.264: 512 kbps and HEVC: 384 kbps) lower in quality than radiologists. However, the difference is less obvious for the higher quality videos. The observed tendencies are further statistically analysed. In the case of the low-quality videos, i.e., H.264: 512 kbps and

HEVC: 384 kbps, a statistical significance test is performed with the quality as the dependent variable and the specialty, i.e., radiologist vs. sonographer, as the dependent variable. As the test for the assumption of normality is not satisfied (i.e., p-value<0.05 for the Shapiro-Wilk test), a nonparametric version (i.e., the Mann-Whitney *u*-test) analogue to an independent samples *t*-test is conducted. The test results (i.e., *u*-value<0.05) indicate that there is a statistically significant difference between radiologists and sonographers in rating low-quality videos. Similarly, in the case of higher quality videos, i.e., H.264: 1000 and 1500 kbps and HEVC: 512, 768 and 1000 kbps, preceded by a test for the assumption of normality, a Mann-Whitney *u*-test is performed and the results (i.e., *u*-value>0.05) reveal that there is no statistically significant difference between radiologists and sonographers in rating higher quality videos.

Fig. 4.3 and Fig. 4.4 show that compression settings – both variables of compression scheme and compression ratio – affect the video quality. Also, the effect tends to be subject to video content, for example, in both cases of radiologists and sonographers, the quality of "Content 1" has consistently been scored higher than the quality of "Content 2", independent of the compression scheme or compression ratio. Now, to further understand the impact of compression and content on video quality, we performed a statistical analysis, i.e., ANOVA (Analysis of Variance). In each case, the perceived quality is selected as the dependent variable, the video content and compression as fixed independent variables and the participant as random independent variable. The two-way interactions of the fixed variables are included in the analysis. The results are summarised in Table 4.1 and Table 4.2 for radiologists and sonographers, respectively, where the F-statistic (i.e., F) and its associated degrees of freedom (i.e., df) and significance (i.e., p-value) are included.

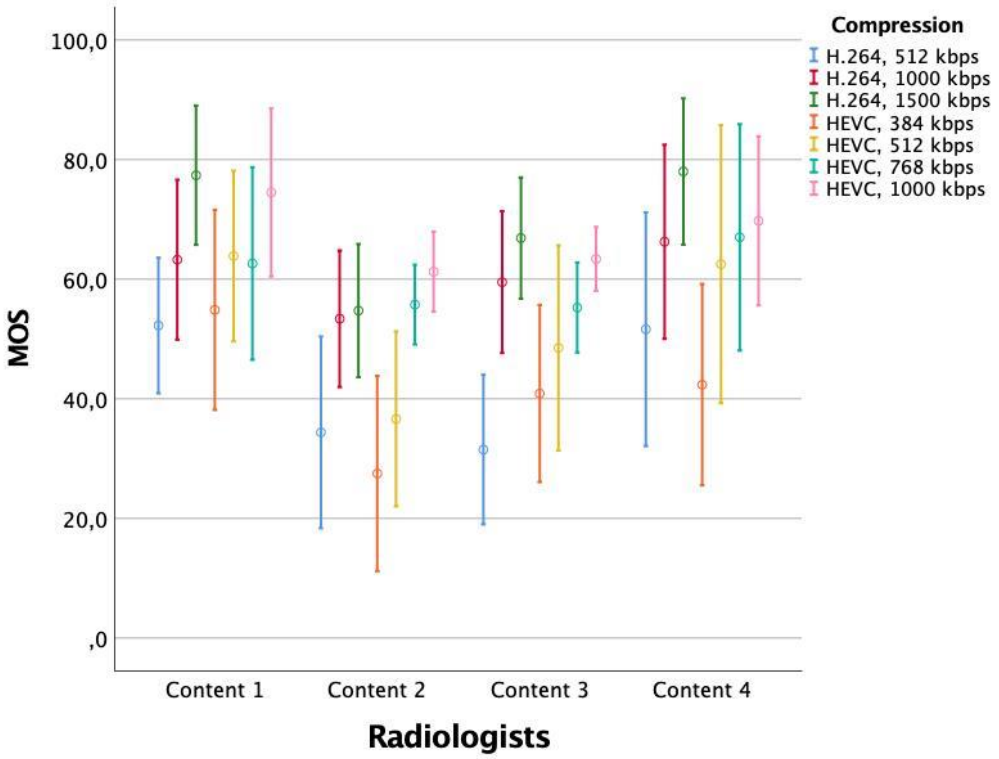


Fig. 4.3: Illustration of the MOS averaged over all radiologists for each compressed video. "Content" refers to a source video. Error bars indicate a 95% confidence interval.

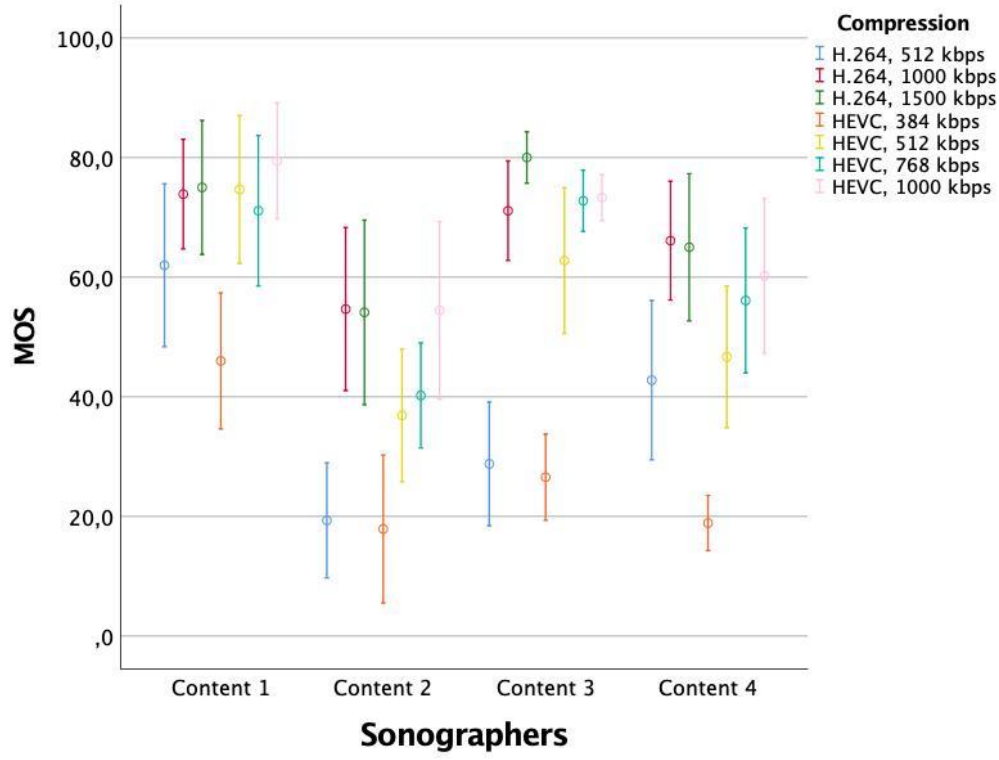


Fig. 4.4: Illustration of the MOS averaged over all sonographers for each compressed video. "Content" refers to a source video. Error bars indicate a 95% confidence interval.

Table 4.1: Results of the ANOVA to evaluate the effect of "Participant", "Content" and "Compression" on the perceived quality for radiologists.

Factor	df	F	p-value
Participant	7	1.365	0.266
Content	3	3.645	0.029
Compression	6	51.520	<0.01
Content * Compression	18	1.495	0.102

Table 4.2: Results of the ANOVA to evaluate the effect of "Participant", "Content" and "Compression" on the perceived quality for sonographers.

Factor	df	F	p-value
Participant	8	1.264	0.306
Content	3	14.324	<0.001
Compression	6	68.959	<0.001
Content * Compression	18	3.862	<0.001

Firstly, in both cases, the results showed that there is no statistically significant difference between participants in scoring video quality (i.e., $p>0.05$ in both cases). Note there is, therefore, little need to calibrate the raw scores using z-scores (as conventionally required for natural image and video quality assessment [100]) due to the consistency in scoring among individuals. This, in turn, reveals that the quality perception behaviour is highly consistent within a specialty group.

Second, the results showed that all main effects (i.e., "Content" and "Compression") are statistically significant in each case. Not all source videos (i.e., "Content") have the same average quality (i.e., $p<0.05$ in both cases). The post-hoc test revealed the following order in quality (note that commonly underlined entries are not significantly different from each other, with the commonly used 5% threshold).

For radiologists:

Content 2 (<MOS> = 46.23) < Content 3 (<MOS> = 52.27) < Content 4 (<MOS> = 62.5) < Content 1 (<MOS> = 64.11).

For sonographers:

Content 2 (<MOS> = 39.65) < Content 4 (<MOS> = 50.83) < Content 3 (<MOS> = 59.33) < Content 1 (<MOS> = 68.87).

Clearly, both radiologists and sonographers scored the quality of "Content 2" on average statistically significantly lower than the quality of other three source contents. “Content 1” tends to receive the highest quality scores in both cases. We can further observe a trend from the “unacceptable” quality scores (i.e., scores that are below 25) given by all participants that the majority of them are from one source video, i.e., eight scores and twelve scores from “Content 2”, five scores and seven scores from “Content 3”, three scores and six scores from “Content 4” and none from “Content 1” within the radiologists’ and the sonographers’ ratings, respectively. This implies that, using the same setting of video compression, “Content 2” is more likely to be affected by distortions. This perception is consistent between the two specialty groups.

Thirdly, in either case, there is also a significant difference (i.e., $p<0.05$ in both cases) in quality between the seven configurations of compression, and the post-hoc analysis revealed the following order in quality.

For radiologists:

HEVC: 384 kbps (<MOS> = 41.41) < H.264: 512 kbps (<MOS> = 42.44) < HEVC: 512 kbps (<MOS> = 52.88) < HEVC: 768 kbps (<MOS> = 60.16) < H.264 1000 kbps (<MOS> = 60.60) < HEVC: 1000 kbps (<MOS> = 67.22) < H.264: 1500 (<MOS> = 69.25).

For sonographers:

HEVC: 384 kbps (<MOS> = 27.33) < H.264: 512 kbps (<MOS> = 38.22) < HEVC: 512 kbps (<MOS> = 55.25) < HEVC: 768 kbps (<MOS> = 60.06) < H.264: 1000 kbps (<MOS> = 66.44) < HEVC: 1000 kbps (<MOS> = 66.86) < H.264: 1500 (<MOS> = 68.53).

The rankings of compression configurations (based on their average quality) tend to be highly consistent between radiologists and sonographers. Again, it is worth noticing here the difference in quality perception of low-quality videos between the two specialty groups. For HEVC: 384 kbps, sonographers score the quality on average much lower (i.e., <MOS> = 27.33) than radiologists (i.e., <MOS> = 41.41); similarly, for H.264: 512 kbps, sonographers' score on the quality is on average lower (i.e., <MOS> = 38.22) than radiologists (i.e., <MOS> = 42.44). This indicates that radiologists show more tolerance of high distortions, whereas sonographers are more sensitive to highly distorted videos. At higher quality, sonographers are in close agreement with radiologists in terms of the average quality.

Finally, we investigate the impact of H.264 versus HEVC on the perceived quality of ultrasound videos. Fig. 4.5 and Fig. 4.6 illustrate the impact of the compression strategy on perceived quality, averaged over all subjects (within a subject group) for radiologists and sonographers, respectively, and all source videos. For both cases, it can be seen that for each compression scheme (i.e., either H.264 or HEVC), the perceived quality monotonously increases with the increase of bit rate. Also, the following observations can be directly interpreted from these figures. For radiologists, at low quality, one can conclude that the bit rate of H.264 (i.e., H.264: 512 kbps) should be 1.3 times as high as the bit rate of HEVC (i.e., HEVC: 384 kbps) to be perceived as equal quality. At high quality, to achieve the same perceived quality, the bit rate of H.264 (i.e., H.264: 1500 kbps) should be 1.5 times the bit rate of HEVC (i.e., HEVC: 1000 kbps). For sonographers, at high quality, to achieve the same perceived quality, the bit rate of H.264 (i.e., H.264: 1000 or 1500 kbps) should be 1 to 1.5 times the bit rate of HEVC (i.e., 1000 kbps).

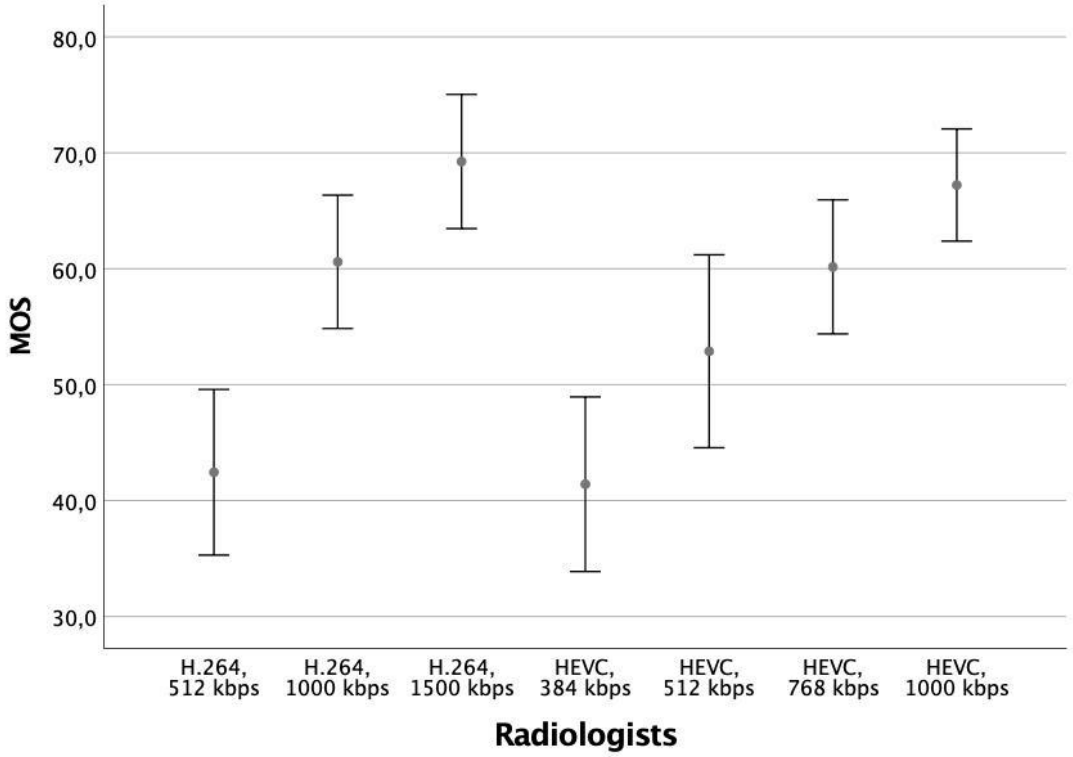


Fig. 4.5: Illustration of the quality averaged over all radiologists and all contents for each compression configuration. Error bars indicate a 95% confidence interval.

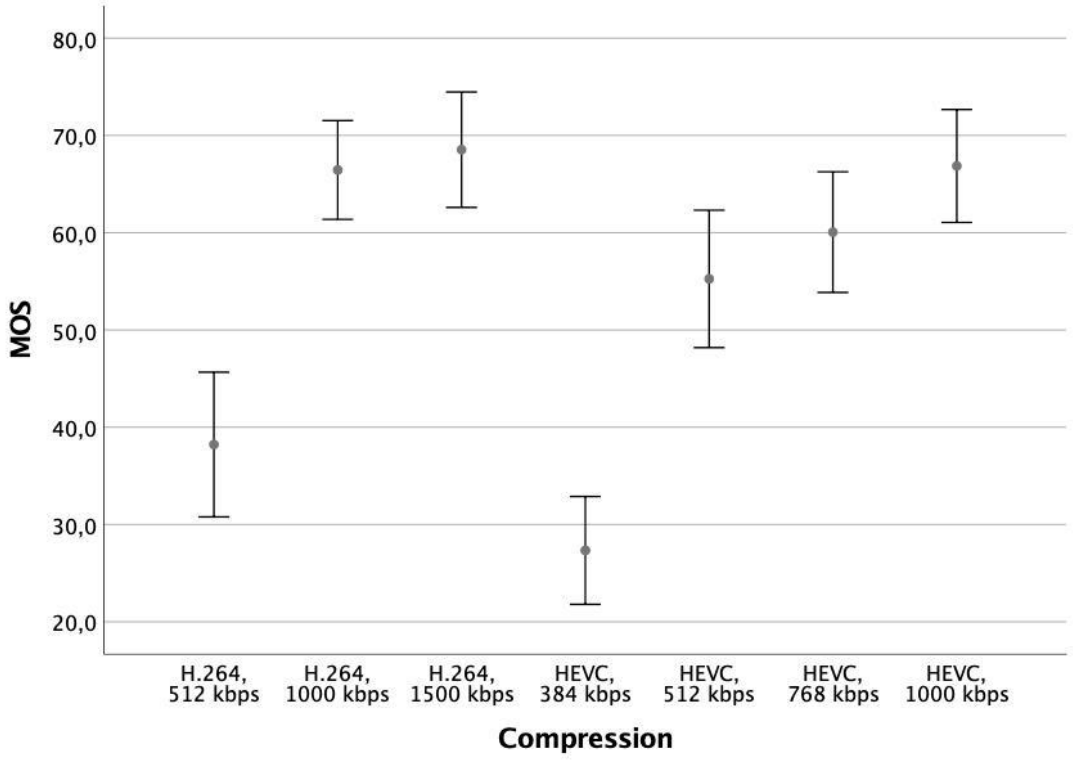


Fig. 4.6: Illustration of the quality averaged over all sonographers and all contents for each compression configuration. Error bars indicate a 95% confidence interval.

Pairwise comparisons are further performed with hypothesis testing between the two compression schemes, H.264 and HEVC. The results are summarised in Table 4.3 for the case of radiologists and Table 4.4 for the case of sonographers, where a nonparametric version analogue to a paired sample *t*-test (i.e., Wilcoxon signed rank sum) is conducted. For radiologists, Table 4.3 clearly indicates that there is no statistically significant difference in perceived quality between H.264: 512 kbps and HEVC: 384 kbps, and that similarly for the following pairwise comparisons: H.264: 1000 kbps vs. HEVC: 768 kbps, and H.264: 1500 kbps vs. HEVC: 1000 kbps, the difference is not statistically significant for each case. For sonographers, Table 4.4 shows that there is no significant difference between H.264: 1000 kbps and H.264: 1500 kbps, and that similarly for the following pairwise comparisons: H.264: 1000 kbps vs. HEVC: 1000 kbps, H.264: 1500 kbps vs. HEVC: 1000 kbps, and HEVC: 512 kbps and HEVC 768 kbps, the difference is not statistically significant for each case.

Table 4.3: Results of the statistical significance for pairwise comparisons (radiologists). Each entry in the table represents a code word consisting of one out of three symbols: "1" means that the configuration for the row is statistically better than the configuration for the column, "0" means that it is statistically worse, and "-" means that it is statistically indistinguishable.

	H.264, 512 kbps	H.264, 1 Mbps	H.264, 1.5 Mbps	HEVC, 384 kbps	HEVC, 512 kbps	HEVC, 768 kbps	HEVC, 1 Mbps
H.264, 512 kbps		0	0	-	0	0	0
H.264, 1 Mbps	1		0	1	1	-	0
H.264, 1.5 Mbps	1	1		1	1	1	-
HEVC, 384 kbps	-	0	0		0	0	0
HEVC, 512 kbps	1	0	0	1		0	0
HEVC, 768 kbps	1	-	0	1	1		0
HEVC, 1 Mbps	1	1	-	1	1	1	

Table 4.4: Results of the statistical significance for pairwise comparisons (sonographers). Each entry in the table represents a code word consisting of one out of three symbols: "1" means that the configuration for the row is statistically better than the configuration for the column, "0" means that it is statistically worse, and "-" means that it is statistically indistinguishable.

	H.264, 512 kbps	H.264, 1 Mbps	H.264, 1.5 Mbps	HEVC, 384 kbps	HEVC, 512 kbps	HEVC, 768 kbps	HEVC, 1 Mbps
H.264, 512 kbps		0	0	1	0	0	0
H.264, 1 Mbps	1		-	1	1	1	-
H.264, 1.5 Mbps	1	-		1	1	1	-
HEVC, 384 kbps	0	0	0		0	0	0
HEVC, 512 kbps	1	0	0	1		-	0
HEVC, 768 kbps	1	0	0	1	-		0
HEVC, 1 Mbps	1	-	-	1	1	1	

4.4 Main findings and contributions

In this chapter, we investigated how different medical specialty groups assess the quality of ultrasound video via a dedicated subjective experiment. We designed and conducted a perception experiment, where videos of different ultrasound exams distorted with various compression schemes and ratios were assessed by both radiologists and sonographers.

For both specialty groups, the impact of visual content and compression configuration (i.e., video codec and bit rate) on the perceived quality of videos is found to be significant. Statistical analyses showed that the way the video quality changes with the content and compression configuration tends to be consistent for radiologists and sonographers, i.e., the perceived quality monotonically increases with the increase of the bit rate.

However, the results demonstrated that for the highly compressed (i.e., H.264: 512 kbps and HEVC: 384 kbps) stimuli, sonographers are more bothered by the distortions than the radiologists; and that for the moderately compressed (i.e., H.264: 1000, and 1500 kbps and HEVC: 512, 768, and 100 kbps) stimuli, radiologists and sonographers behave similarly in terms of their quality of visual experience.

Finally, the impact of the compression scheme (i.e., H.264 vs. HEVC) was analysed. The results showed that, for radiologists, the bit rate of H.264 for highly compressed videos should be 1.3 times the bit rate of HEVC to be perceived similarly, whereas it should be 1.5 times the bit rate of HEVC for lower compression. For sonographers, the bit rate of H.264 should be 1 to 1.5 times the bit rate of HEVC to achieve the same perceived quality at high quality.

Chapter 5:
Study of visual attention in screening mammography

5.1 Introduction

In Chapters 3 and 4, we studied how medical professionals perceive the quality of medical visual content, as well as the impact of the specialty settings on the quality of experience. Another essential component of the human visual system (HVS) is visual attention, which refers to the process that enables to efficiently select the most relevant information from a visual scene [14].

Understanding visual attention is primordial in medical imaging, as healthcare professionals look at specific areas in images in order to render a diagnosis. Three different types of erroneous decisions in radiology are described in the literature: search errors, recognition errors and decision-making errors [5], [63], [102]. Perceptual errors, or errors made during the detection and recognition phases, are more frequent than interpretative errors in radiology [103]. These findings were confirmed for the mammography specialty by Nodine et al. [104] in a study involving missed lesions on twenty breast cancer cases.

Screening mammography has been widely used over the last few decades to detect early breast cancer by use of low-dose X-ray imaging. Indeed, being able to detect early breast lesions is highly beneficial for patients as it increases the likelihood of cancer being successfully treated and increases the chance of recovery. Mammography is therefore a useful but highly challenging modality in medical imaging [105]. Breast cancer is the most common type of cancer in Europe and there are twice as many new breast cancer cases annually than new cancer cases in any other site [106]. It is an important mortality cause for women over fifty years old.

Eye-tracking technology can play an important role in understanding why lesions are missed in radiology for instance, by unravelling the visual search process. In a typical eye-tracking study, radiologists are asked to view images and report abnormalities as

they normally do in clinical practice while their eye positions and eye movements are recorded using an eye-tracking system. A variety of eye-tracking studies have been undertaken in the area of mammography. These studies present different concepts of experimental design; some studies are conducted with films, some with digitised films, and some with fully digital mammograms; images are obtained from public screening databases or from specifically selected cases; and stimuli are displayed on laptops or monitors for viewing. In the literature, Kundel et al. [59] gathered eye-tracking data from three different public databases, including a total of 400 eye movement records from experienced mammographers, mammography fellows, and radiology residents viewing mammograms with and without lesions. Their main finding was that 67% of cancer locations were fixated within the first second of viewing; and they suggested that the observers should use a global approach when searching for cancer in mammograms. Studies in the literature are often limited in terms of stimuli or number of participants. Furthermore, little work has been done to compare different views of mammograms used in routine practice.

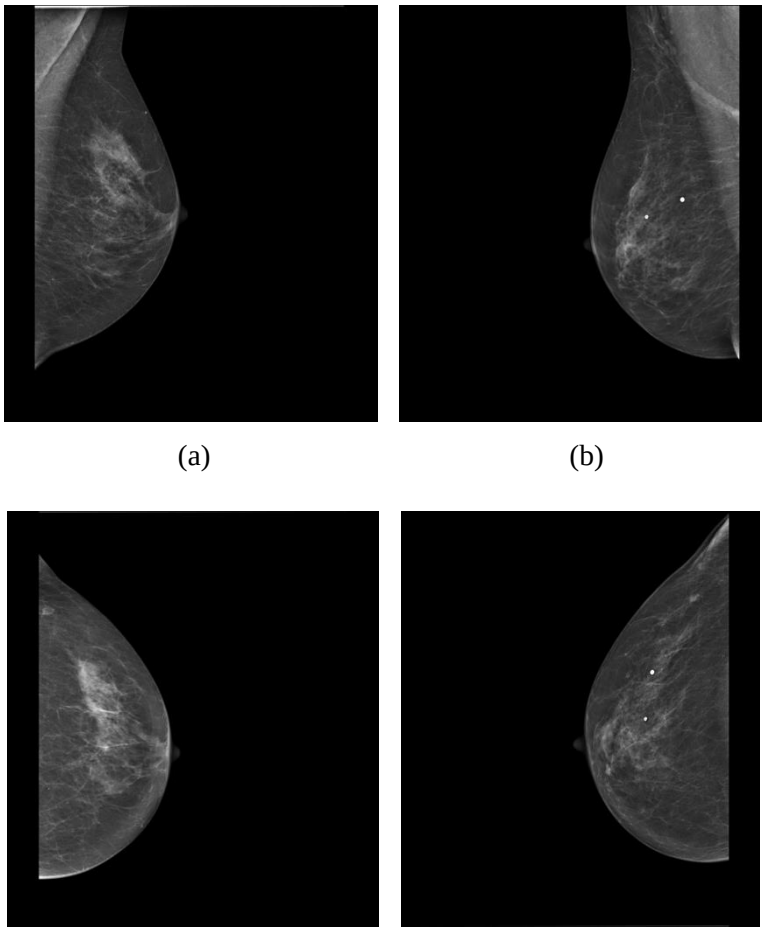
In this chapter, we want to study how attention is allocated between different mammogram views to better understand how radiologists perceive and interpret mammograms, and use such understanding to improve clinical practice in screening mammography.

5.2 Eye-tracking experiment

5.2.1 Stimuli

In practice, mammograms are usually captured from several views in order to yield a better diagnosis. Two widely used views are the cranio-caudal (CC) and the medio-lateral oblique (MLO) views. For each breast, a CC view is taken horizontally (i.e., with a 0-degree angle), whereas a MLO view is taken diagonally (i.e., with a 45-degree angle). The MLO views thus display a broader portion of breast tissue.

The stimuli used in our eye-tracking experiment consist of 392 mammogram images from 98 anonymised patients. Each patient's case is indeed composed of two CC views (i.e., left and right breast) and two MLO views (i.e., left and right breasts). The mammograms were acquired from the University Hospitals KU Leuven in Belgium. All the cases were known to be lesion-free, however, participants were not informed of these indications to be encouraged to consider all plausible diagnoses when viewing the images. Fig. 5.1 represents an example of the CC and MLO views of a patient. All images were linearly downscaled to a resolution of 1080×1920 pixels to enable a controlled experiment.



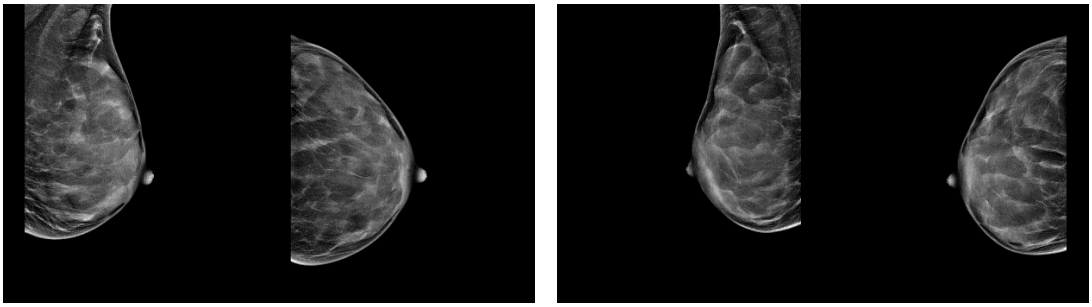
(a) (b)

(c) (d)

Fig. 5.1: Illustration of four sample stimuli taken from the same patient used in our experiment: (a) MLO view of the left breast, (b) MLO view of the right breast, (c) CC view of the left breast, and (d) CC view of the right breast.

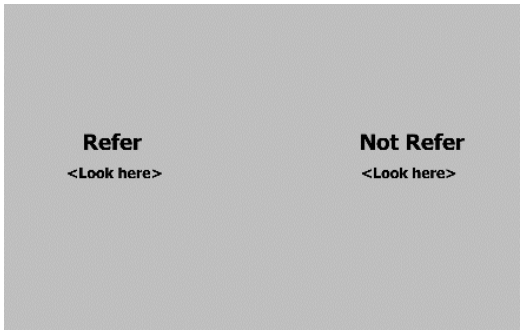
5.2.2 Experimental procedure

In routine practice, radiologists analyse both views (i.e., MLO and CC) of a breast at the same time to make diagnostic decisions. This configuration was simulated in our experiment, where the MLO and CC views of the left breast were presented first to the radiologists for eight seconds, followed by the MLO and CC views of the right breast for the same amount of time. After viewing the four views of a case, the radiologists had to answer the question "refer or not refer" by focusing on one of these options on the screen. This question was defined in accordance with the practice of routine screening mammography, where radiologists decide if they report the image as suspicious of containing abnormalities. The test configuration is illustrated in Fig. 5.2.



(a)

(b)



(c)

Fig. 5.2: Illustration of the experimental procedure: (a) MLO and CC views of the left breast, (b) MLO and CC views of the right breast, and (c) question asked to the radiologists after viewing (a) and (b).

The images were displayed on a 19-inch LCD monitor screen calibrated to the DICOM Greyscale Standard Display Function (GSDF) [99]-[101]. The eye-tracking experiment was carried out in a mammography reading room, i.e., in a controlled viewing environment. The distance between the observer and the monitor was

maintained at around 60 cm. The eye movements and positions of the participants were recorded using a non-invasive SensoMotoric Instrument (SMI) Red-m advanced eye-tracking device at a sampling rate of 250 Hz. At the beginning of each session, the eye-tracker was calibrated using a nine-point calibration. Prior to the start of the actual experiment, each participant was given written instructions about the procedure. Moreover, a training session was carried out to allow the participants to familiarise themselves with the stimuli and the question asked after each case. The stimuli used during the training session were different from those used for the real experiment.

5.2.3 Participants

Eight radiologists from Breast Test Wales, Cardiff, United Kingdom, participated in the eye-tracking experiment, hereafter referred to as R1 to R8, having one, two, six, eight, eight, twenty, twenty, and twenty-five years of experience in mammography, respectively. All the radiologists who were involved in the experiment had normal or corrected-to-normal vision.

5.3 Experimental results

5.3.1 Number and duration of fixations

Using SMI BeGaze^{TM} Analysis Software, gaze information was extracted directly from the raw eye-tracking data collected during the experiments. These data include the number of fixations for each stimulus, their coordinates, and their duration. A fixation was rigorously defined by SMI's software using the dispersal and duration-based algorithm established in [107], with a minimum duration of 100 ms.

Fig. 5.3 shows the number of fixations averaged over all stimuli and for all radiologists. It can be seen from the figure that the radiologists generally allocated more attention to the MLO views than the CC views. This may be attributed to the fact that the MLO view represents a broader portion of the breast tissues and thus needs more observation from the readers.

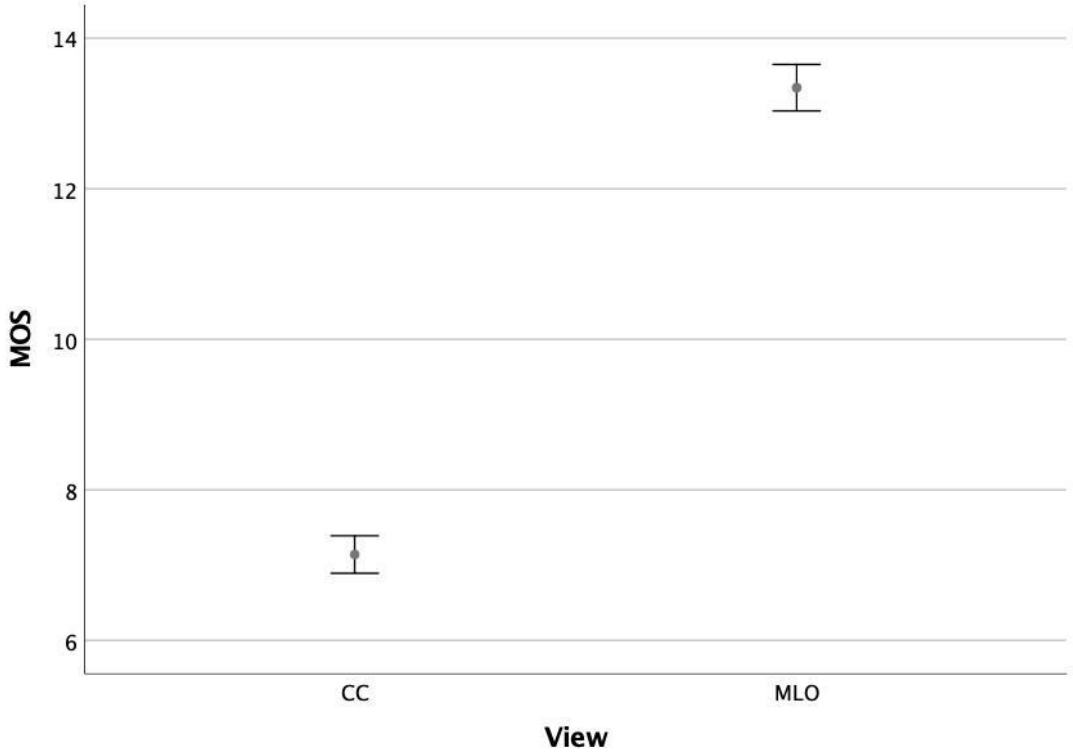


Fig. 5.3: Illustration of the number of fixations averaged over all stimuli, left and right breasts, and all participants for each view (i.e., MLO and CC). Error bars indicate a 95% confidence interval.

Similarly, Fig. 5.4 represents the average number of fixations for the CC views of right and left breasts and MLO views of right and left breasts. Table 5.1 gives the results of the ANOVA conducted to analyse the impact of the view (i.e., MLO and CC), and the impact of the breast (i.e., left or right) on the number of fixations. The results show that there is a significant difference between the CC and MLO views (i.e., p-value<0.05), but there is no statistically significant difference between the left and right breasts (i.e., p-value>0.05).

Table 5.1: Results of the ANOVA to evaluate the effect of "View" and "Breast" on the number of fixations.

Factor	df	F	p-value
View	1	935.92	<0.001
Breast	1	0.719	0.397
View * Breast	1	1.878	<0.001

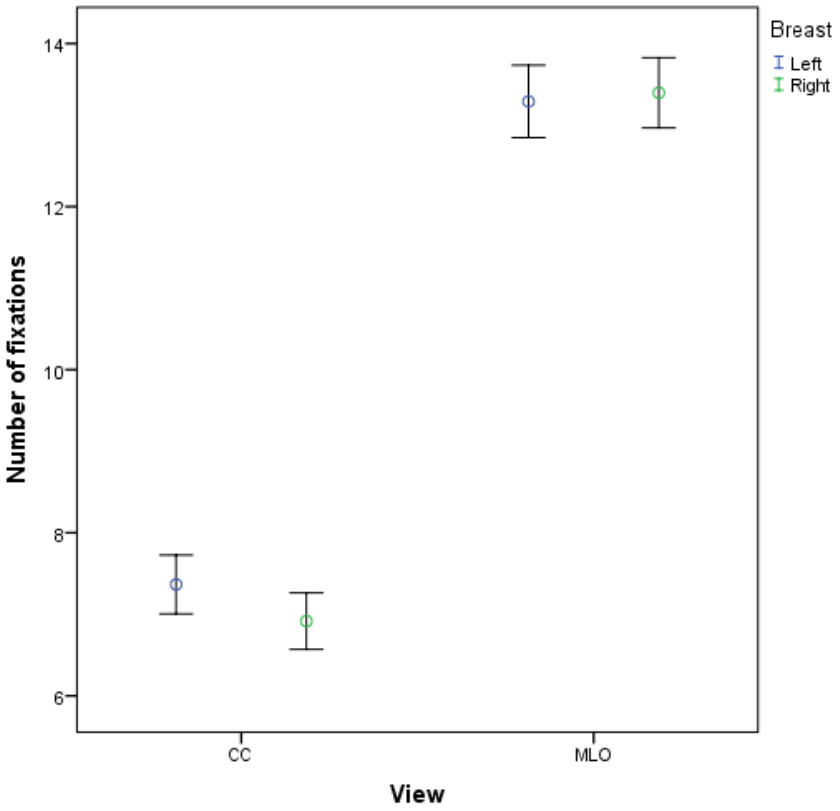


Fig. 5.4: Illustration of the number of fixations averaged over all stimuli and all participants for left breast CC view, right breast CC view, left breast MLO view, and right breast MLO view. Error bars indicate a 95% confidence interval.

Nonetheless, the number of fixations analysed previously does not give any information about the dwell time: a subject could spend many short fixations on an image or, on the contrary, only a few but long fixations on this image.

Fig. 5.5 shows the mean duration of fixations recorded over all stimuli and all radiologists for CC and MLO views. The mean duration of fixations μ_i for a radiologist i is defined as follows:

$$\mu_i = \frac{1}{n}\sum_{j=1}^{n} x_j$$

where n is the total number of fixations and x_j is the duration of the fixation j.

The average duration of fixations over all the eight radiologists is defined as follows:

$$\mu = \frac{1}{8}\sum_{i=1}^{8} \mu_i$$

with μ_i as previously described for a radiologist *i*.

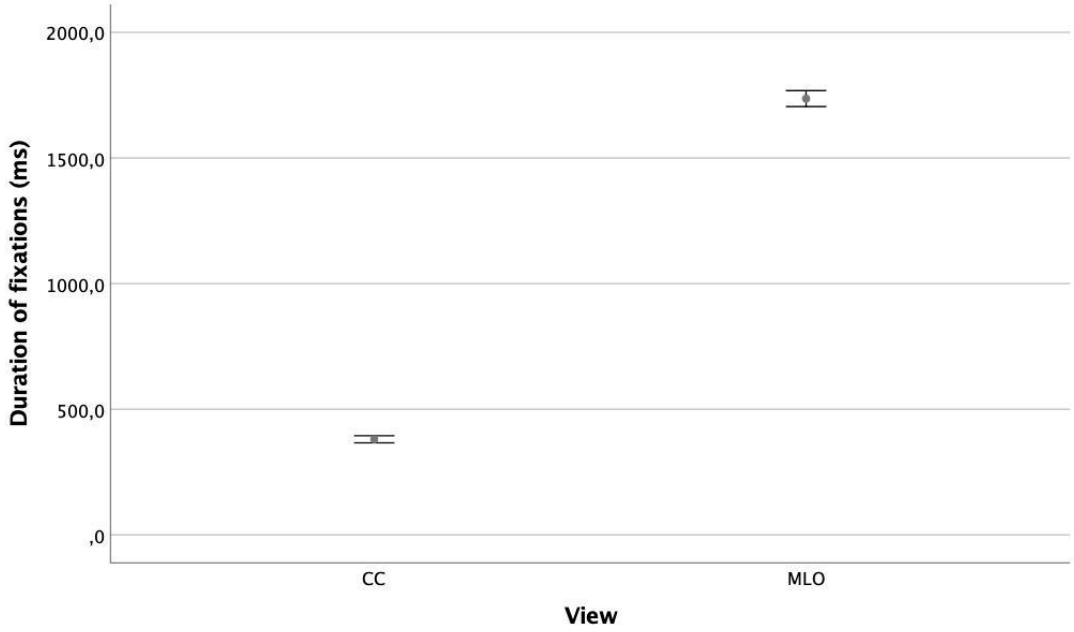


Fig. 5.5: Illustration of the duration of fixations averaged over all stimuli, and all participants for each view (i.e., MLO and CC). Error bars indicate a 95% confidence interval.

Fig. 5.6 illustrates the mean duration of fixations recorded over all stimuli and all radiologists for the CC views of left and right breasts and for the MLO views of left and right breasts.

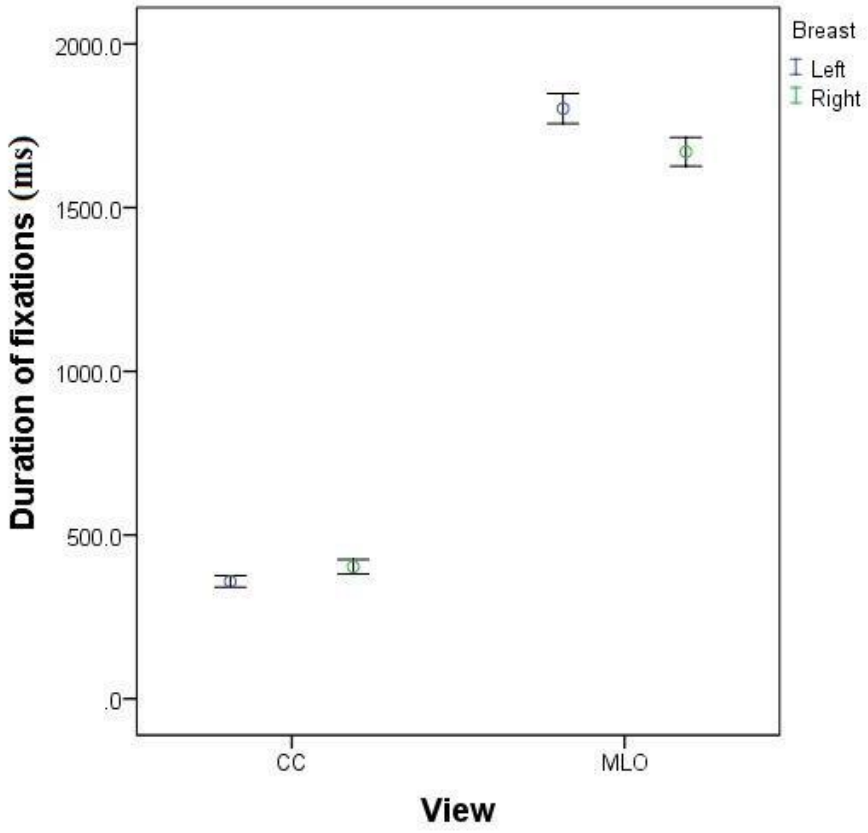


Fig. 5.6: Illustration of the duration of fixations averaged over all stimuli, and all participants for left breast CC view, right breast CC view, left breast MLO view, and right breast MLO view. Error bars indicate a 95% confidence interval.

It can be clearly seen from the Fig. 5.5 and Fig. 5.6 that the MLO attracted longer dwell times from readers than the CC views. This tendency is further analysed with an ANOVA, and results are presented in Table 5.2. Similar to the conclusions obtained for the number of fixations, there is a statistically significant difference between the MLO view and the CC view (i.e., p-value<0.05), but there is no significant difference between the left breast and the right breast (i.e., p-value>0.05).

Table 5.2: Results of the ANOVA to evaluate the effect of "View" and "Breast" on the duration of fixations.

Factor	df	F	p-value
View	1	3488.21	<0.001
Breast	1	3.61	0.057
View * Breast	1	14.822	<0.001

5.3.2 Fixation deployment

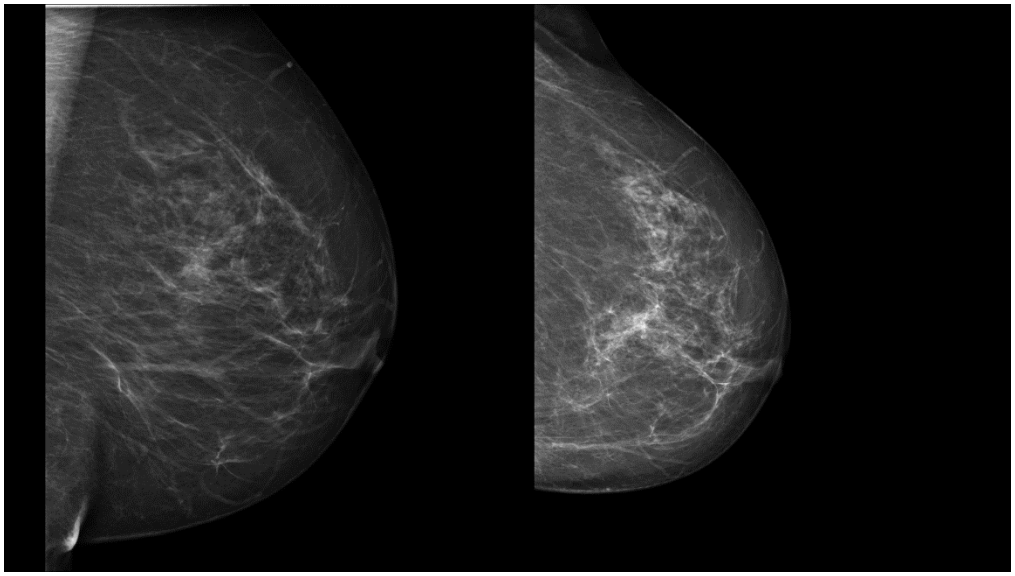
In the area of computer vision, researchers focus on the deployment of fixation locations, and aim to automatically predict where people look in images. To do this, eye-tracking data is often used to generate a so-called saliency map, i.e., a topographic representation indicating conspicuousness of scene locations [108]. Therefore, in a given saliency map, the salient regions (i.e., regions with higher density of fixations) represent where human observers focus their gaze with a higher frequency.

A saliency map is thus created using the fixations obtained from eye-tracking experiments, with each fixation location giving rise to a greyscale patch simulating the foveal vision of the human visual system. The activity of the patch is modelled as a Gaussian distribution. We use the full width at half maximum (FWHM) of a Gaussian to approximates the size of the fovea (i.e., two degrees of visual angle) [109]. Note alternative approximation methods or choice of visual angle may be used; this may affect the local intensity of salient regions in a saliency map but does not significantly alter the global distribution of these salient regions. Investigating the impact of the simulation of the fovea (e.g. using different parameters of a Gaussian or difference choices of visual angle) on the comparison (either subjective or objective) of saliency maps is outside the scope of this thesis. A saliency map over all fixations of all subjects can be calculated as follows:

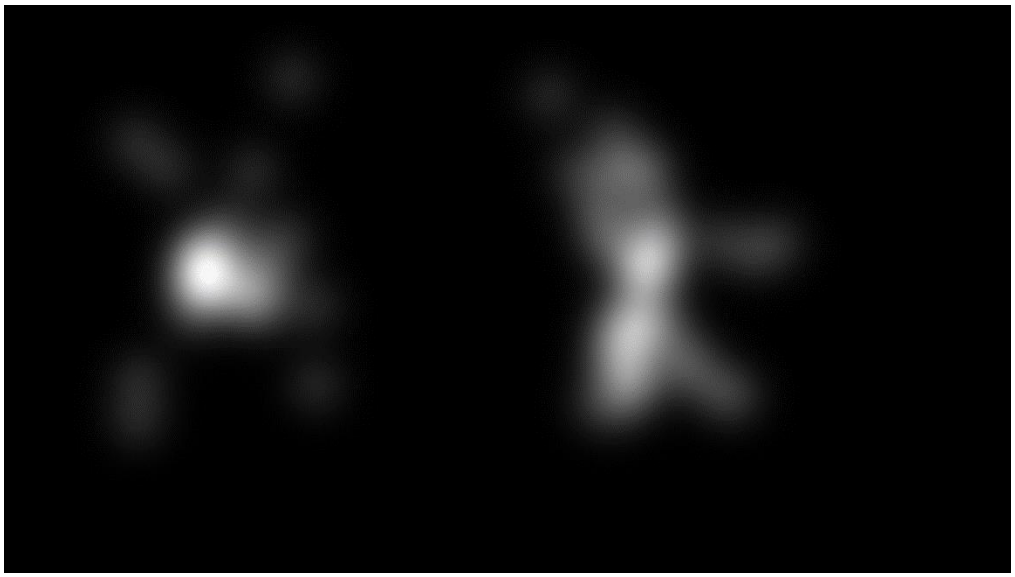
$$SM_i(k,l) = \sum_{j=1}^{T} \exp\left(-\frac{\left(\mathrm{x_j} - k\right)^2 + \left(y_j - l\right)^2}{\sigma^2}\right)$$

where $SM_i(k, l)$ indicates the saliency map for the stimulus I_i; (x_j, y_j) indicates the spatial coordinates of the *j*th.tn fixation (j = 1…T); *T* is the total number of all fixations over all subjects; and σ indicates the standard deviation of the Gaussian, and is determined when the FWHM is equal to the projection of two degrees of visual angle on the screen [110].

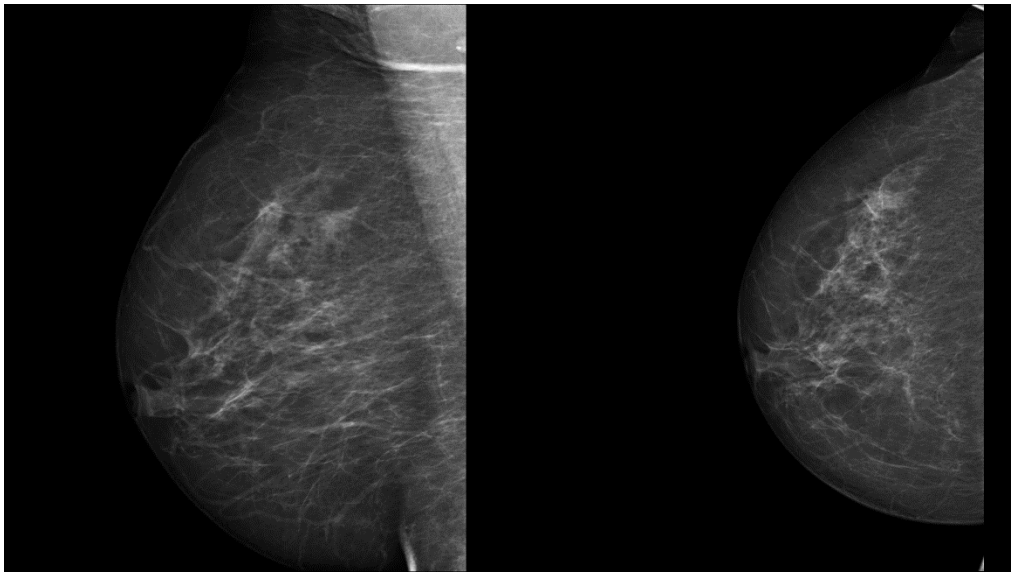
Fig. 5.7 represents the saliency maps created from our eye-tracking data for two patient cases. From the saliency maps, we can see how the attention is allocated between the MLO views (on the left), and the CC views (on the right). In general, the MLO views attracted more attention from the readers as the left images contain more white areas (the brighter the regions, the higher the saliency).



(a)



(b)



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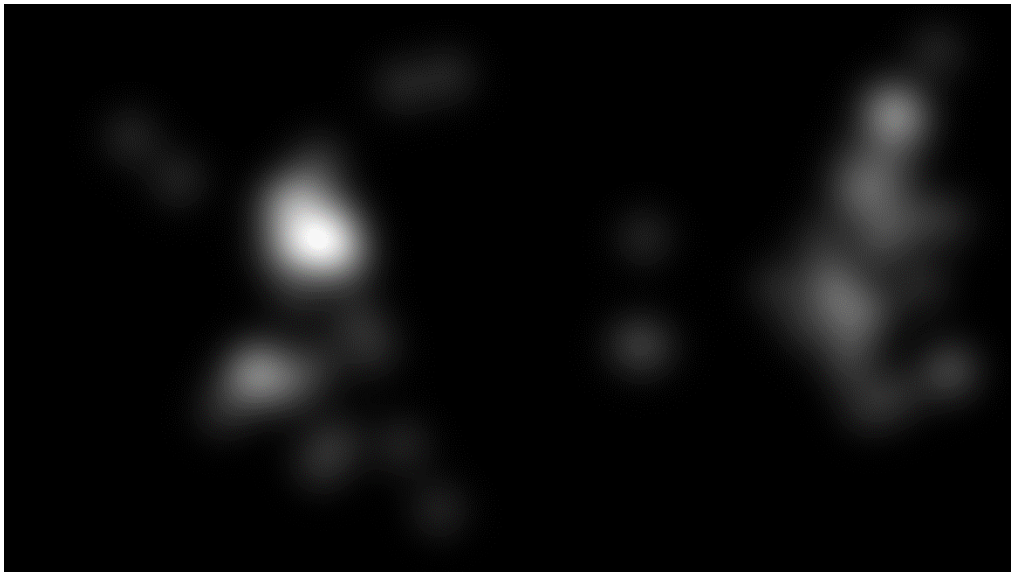
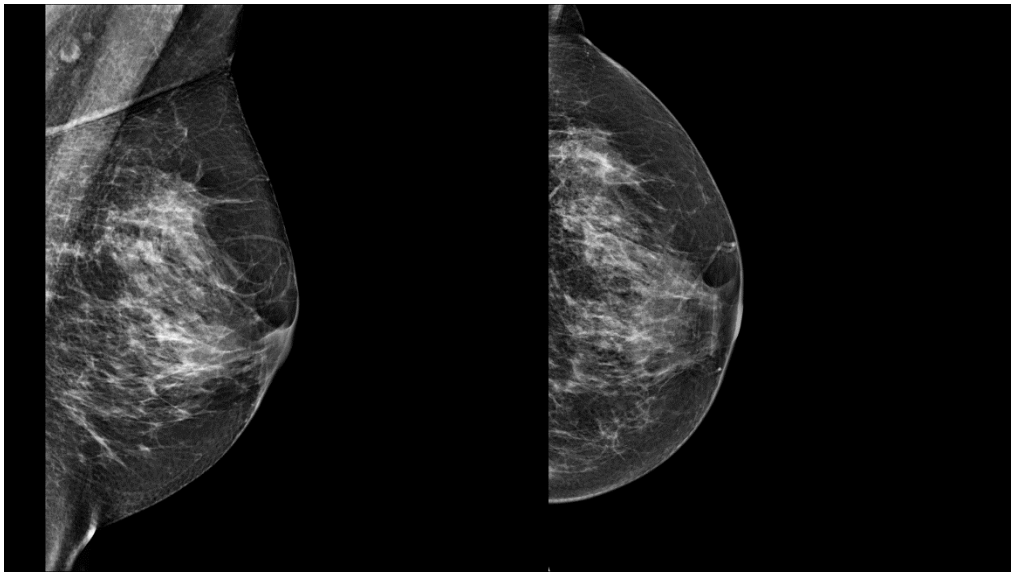
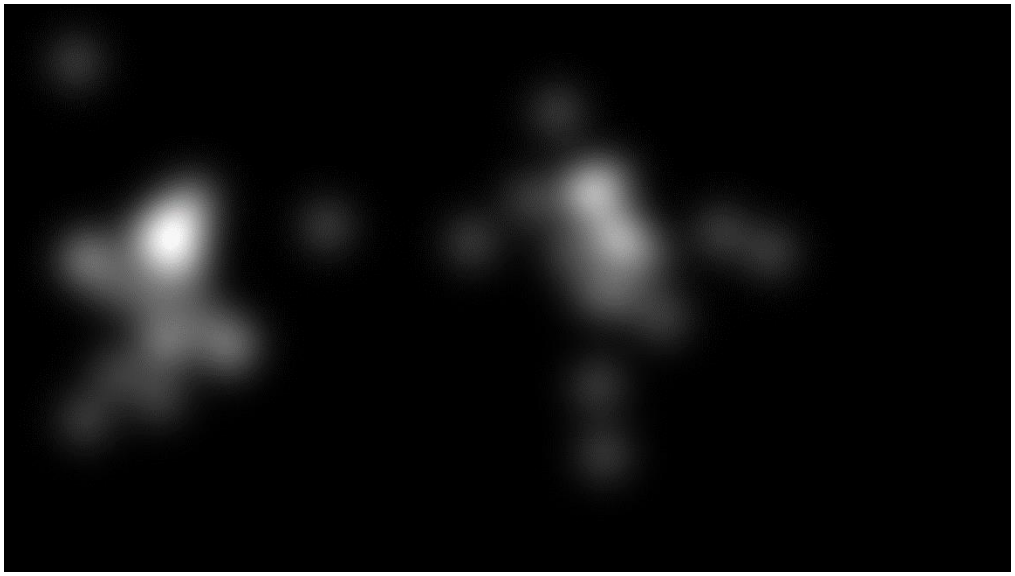


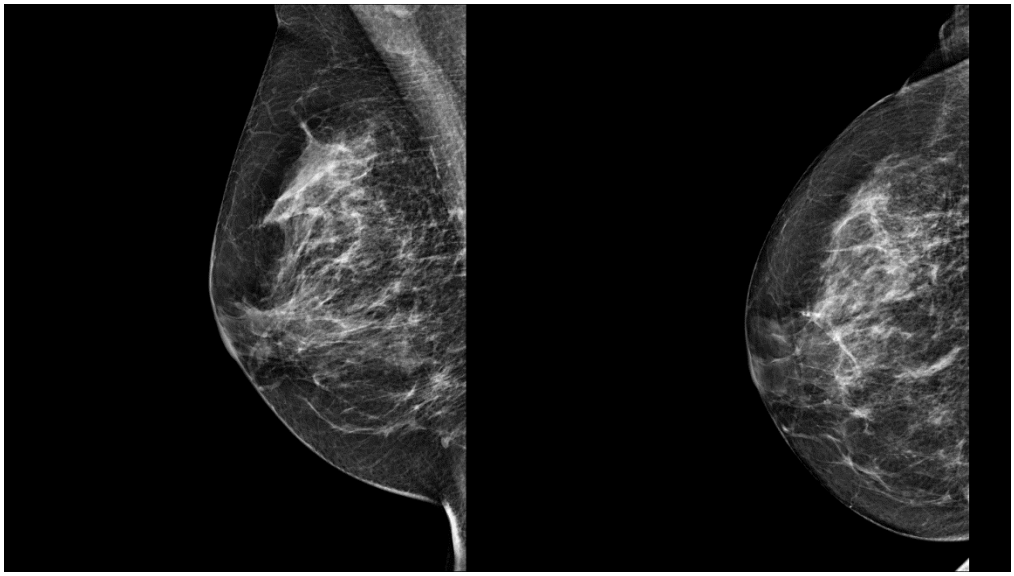
(d)



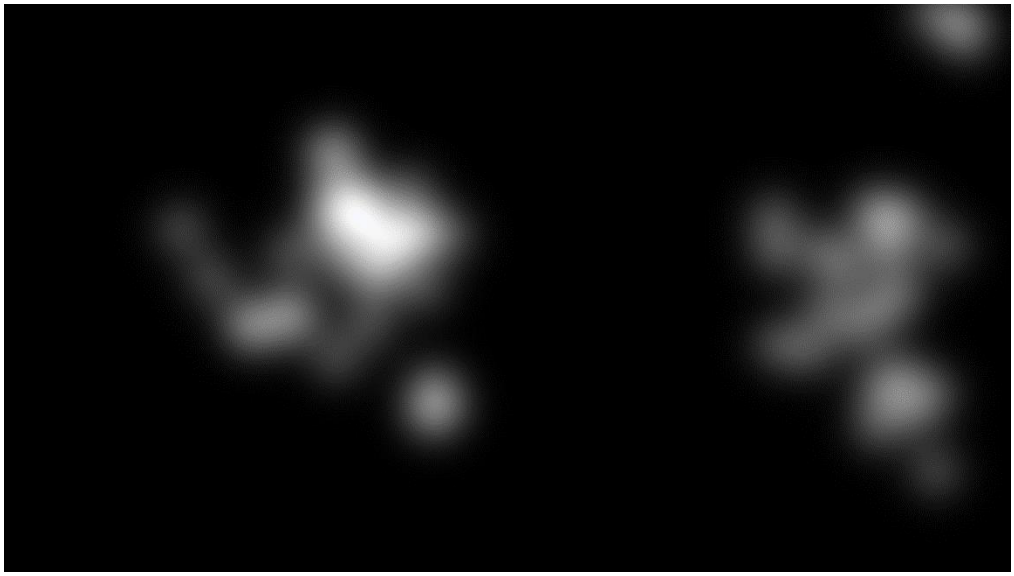
(e)



(f)



(g)

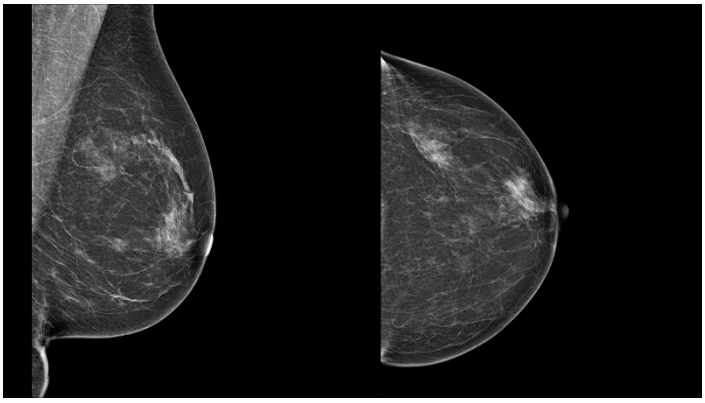


(h)

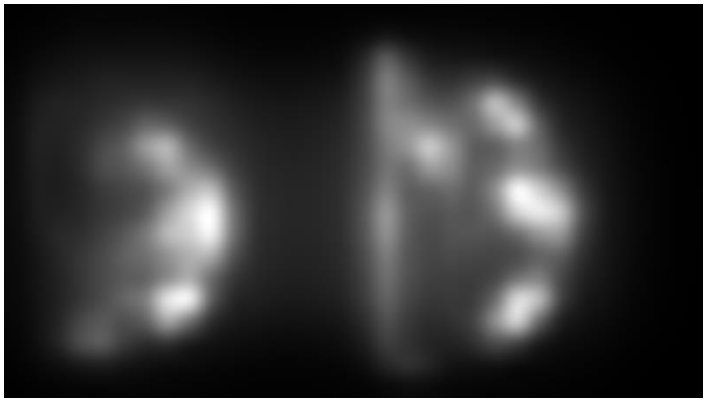
Fig. 5.7: Illustration of the saliency maps constructed for two patient cases: (a) patient 1, MLO and CC views of the left breast, (c) patient 1, MLO and CC views of the right breast, (e) patient 2, MLO and CC views of the left breast, (g) patient 2, MLO and CC views of the right breast; (b), (d), (f), and (h) are the saliency maps of (a), (c), (e), and (g), respectively.

5.3.4 Computational saliency

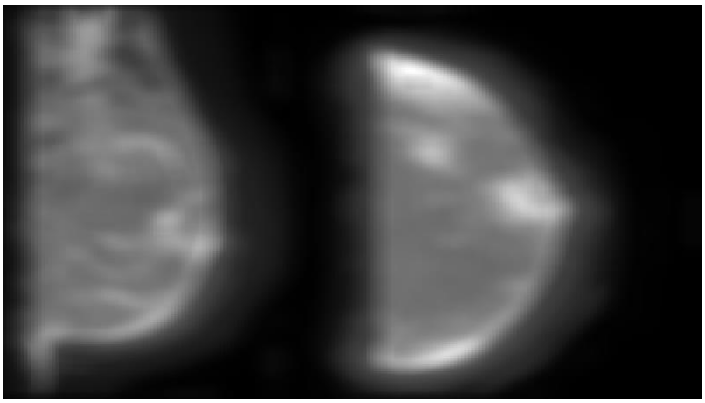
Eye-tracking is useful, but it can be cumbersome and impractical in many circumstances. A more realistic way to integrate gaze information into imaging systems is to use computational saliency. Saliency models, which aim to predict visual saliency of images, are available in the literature [111]. These models were developed for different applications, e.g., object detection; however, very little is known about whether these models are directly applicable to medical imaging and, more specifically, to screening mammography. To investigate above issue, an evaluation was carried out using three state-of-the-art saliency models, namely Graph Based Visual Saliency model (GBVS) [112], Itti [113], and RARE2012 [114]. The GBVS model is a bottom-up visual saliency model composed of two steps including the formation of activation maps and their normalisation to highlight conspicuity. Itti's model was inspired by the neuronal architecture of the primate visual system. Attended locations are selected by a neural network. Finally, RARE2012 selects information based on a multi-scale spatial rarity. Fig. 5.8 shows the computational saliency maps generated by these three widely used saliency models for two sample stimuli contained in our dataset. It can be seen from the figure that the saliency models do not precisely match with the ground truth (i.e., the "human attention").



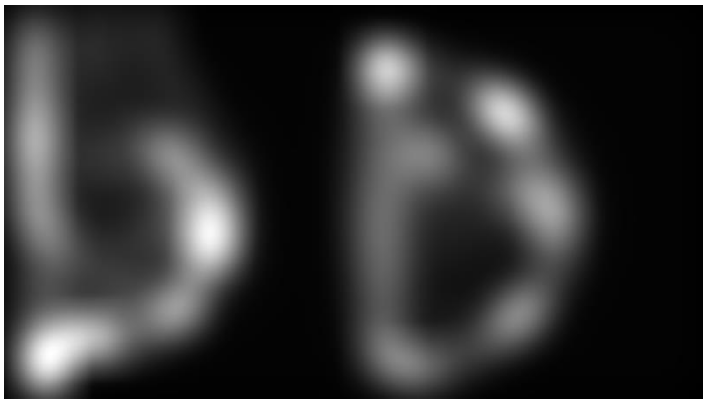
(a)



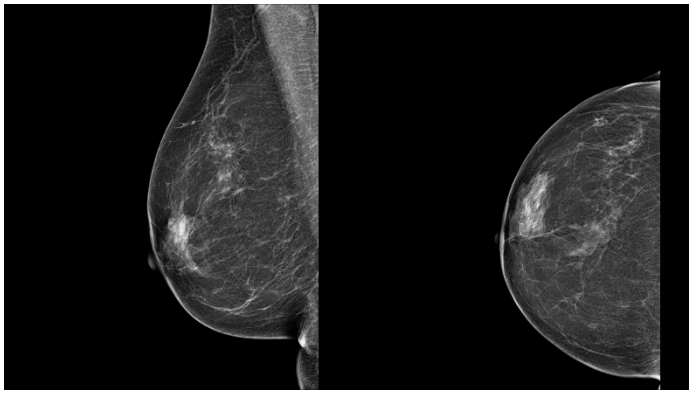
(b)



(c)



(d)



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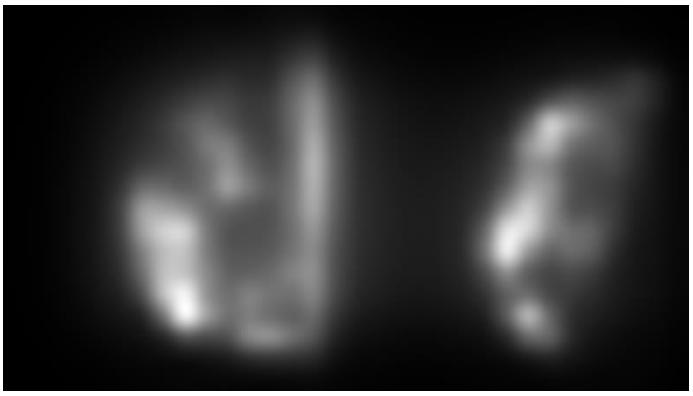
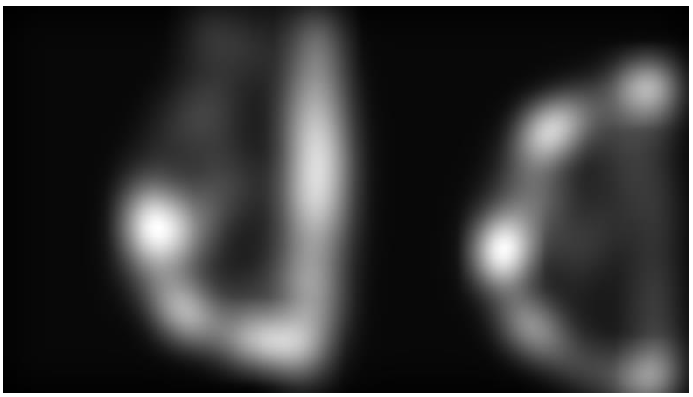
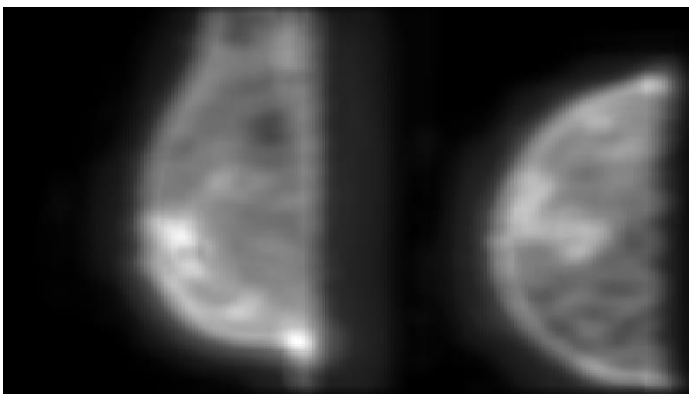


(f)



(g)



(h)

Fig. 5.8: Illustration of the computational saliency maps generated by three state-of-the-art models for two sample stimuli from a patient' case: (a) and (e) represent the original stimuli, (b) and (f) the maps generated with GBVS, (c) and (g) the maps generated by Itti, and (d) and (h) the maps generated by RARE2012.

To quantify the similarity between saliency maps, three evaluation metrics are commonly used: the Pearson's Correlation Coefficient (CC), the Normalised Scanpath Saliency (NSS) and the Area Under ROC (Receiver Operating Characteristic) Curve (AUC) [115]. The CC is a statistical method usually used to evaluate the linear relationship between two distributions. This metric is symmetric and similarly penalises false positives and negatives, and is invariant to linear transformations. The idea behind the NSS is to quantify the saliency map values at the eye fixation locations and to normalise it with the saliency map variance [116] as follows:

$$NSS(p) = \frac{SM(p) - \mu_{SM}}{\sigma_{SM}}$$

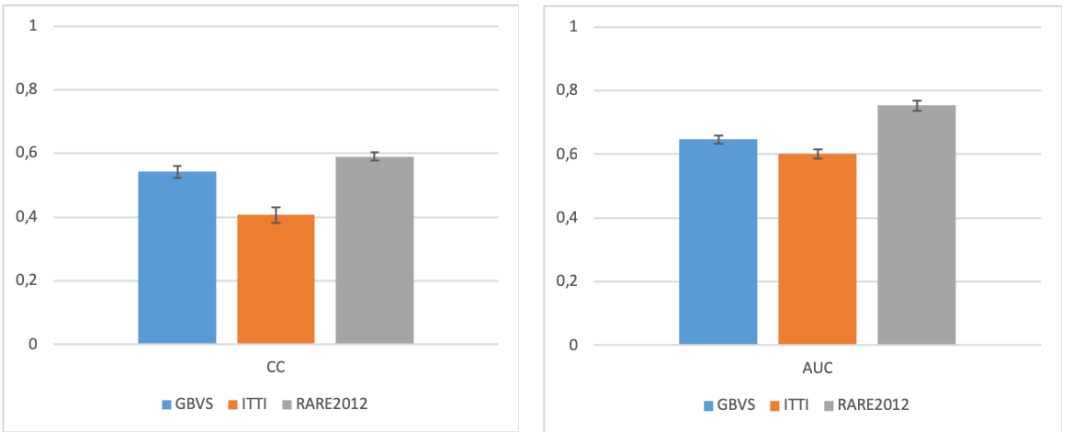
where *p* is the location of one fixation and *SM* is the saliency map which is normalised to have a zero mean and unit standard deviation. The *NSS* score is the average of *NSS(p)* for all fixations:

$$NSS = \frac{1}{N}\sum_{p=1}^{N} NSS(p)$$

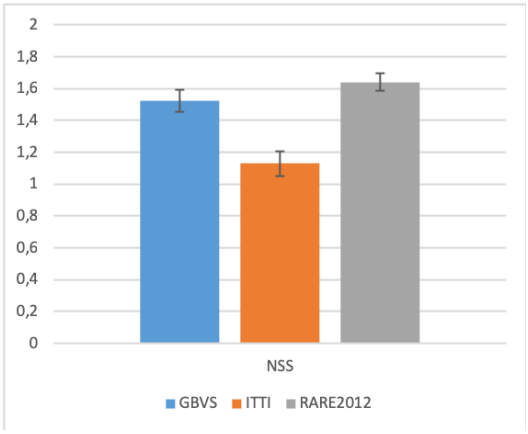
where N is the total number of eye fixations. Finally, the AUC is the most widely used metric to evaluate saliency maps. This metric treats a given saliency map as a binary classifier of fixations at various threshold values [115]. A ROC curve is generated by measuring the true and false positive rates under each binary classifier.

To summarise, when CC is close to -1 or 1, the similarity is high, whereas it is low when CC is close to 0. When NSS>0 or AUC>0.5, the similarity measure is significantly better than chance, and the higher the value is, the more similar are the variables.

Fig. 5.9 illustrates the similarity measures between human and modelled saliency averaged over all stimuli in our database. In general, the CC, NSS and AUC values show a limited correlation with human attention (e.g., CC values are about half their maximum value). This can be explained by the fact that models are based on a bottom-up approach, whereas medical imaging involves a task, i.e., a top-down component. In general, RARE2012 performed better than GBVS and Itti models. This suggests that a more accurate saliency modelling is needed to better predict the viewing behaviour of radiologists when evaluating mammograms.



(a) (b)



(c)

Fig. 5.9: Illustration of the similarity measures between human and modelled saliency averaged over all the stimuli using the CC (a), AUC (b), and NSS (c) metrics.

5.4 Main findings and contributions

In this chapter, we presented a large-scale eye-tracking study where 196 combined views of cranio-caudal and medio-lateral oblique mammograms were assessed by eight radiologists.

The eye-tracking data obtained from the radiologists were analysed, using the number and duration of fixations. The results showed that the radiologists spent more attention and more time on the MLO views than on the CC views. For both metrics, the results showed that there is a statistically significant difference between the MLO and CC views.

We also analysed the fixation deployment for the MLO and CC views when displayed simultaneously. Radiologists' gaze data were compared with three state-of-the-art models of visual attention. Similarity measures (i.e, Pearson correlation coefficient, normalised scanpath saliency, and area under ROC curve) showed the poor correlation between these models' predictions and the human attention, and we thus demonstrated the need for improvement of computational attention models to reliably predict radiologists' gaze behaviour.

Chapter 6:
Impact of the medical specialty and experience on image readers gaze behaviour

6.1 Introduction

As demonstrated in Chapter 5, eye-tracking technology can be used to study the gaze patterns of medical experts while reading radiological content. In the literature review given in Chapter 2, it has also been shown that eye movements could be used to distinguish medical experts and novices. In practice, a broad community of readers is involved in medical image analysis as readers have diverse specialised training or experience. For example, radiologists are specialised in the interpretation of clinical imaging and focus on lesion research and recognition. Medical physicists apply physics to provide clinical services in diagnosis, managing the technological components of radiology. Therefore, both radiologists and physicists deal with mammograms in their practice, but for different purposes.

In this chapter, we perform statistical analysis to investigate whether and how the medical specialty practice and the degree of experience affect the gaze behaviour through an eye-tracking experiment with a large number of mammogram images.

6.2 Eye-tracking experiment

6.2.1 Stimuli

As mentioned in Chapter 5, screening mammography usually involves capturing two views: one from above the breast, the cranio-caudal (CC) view, and one from an angled view, the medio-lateral oblique (MLO) view. As the MLO view is taken using a lateral projection, most of the breast tissues can be imaged and thus a more reliable diagnosis can be rendered. Furthermore, we demonstrated in Chapter 5 that readers spent more effort on analysing the MLO images. For that reason, we focus on MLO views in this chapter.

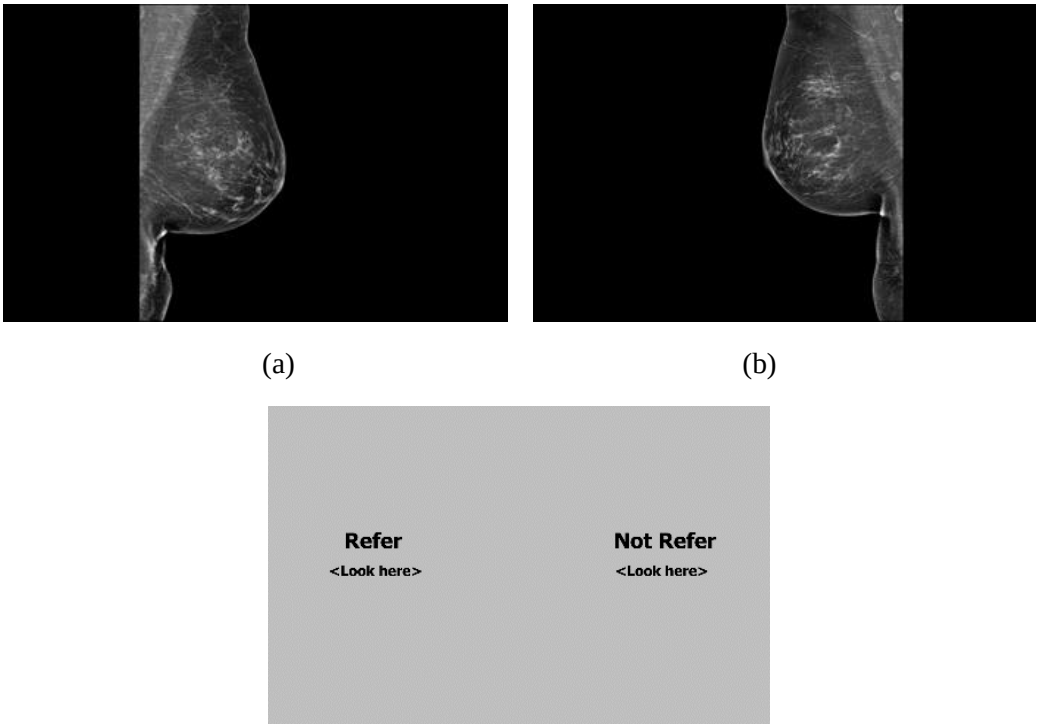
The source images used in our experiment are composed of 196 MLO views from 98 patients, i.e., 98 MLO views of left breasts and 98 MLO views of the corresponding right breasts. The mammograms were acquired from 98 anonymised cases from the University Hospitals KU Leuven, Belgium, and are all known to be lesion-free. Fig. 6.1 represents an example of two stimuli (i.e., left and right breasts of the MLO view) from a patient's case used in our eye-tracking experiment. The original resolution of the mammograms was either 2080×2800 pixels or 2800×3518 pixels. With a view to perform a controlled eye-tracking study, all stimuli were linearly downscaled with MATLAB *imresize* function using bicubic interpolation to fit our screen resolution of 1080×1920 pixels.

Fig. 6.1: Illustration of sample stimuli (i.e., left and right breasts of the MLO view) used in our eye-tracking experiment.

6.2.2 Experimental procedure

The participants were presented the 98 cases in a random order. Both left and right MLO views were presented for a given case: the MLO view of the left breast was displayed first, followed by the MLO view of the corresponding right breast. Each stimulus was displayed for three seconds on a 19-inch LCD monitor screen calibrated to the Digital Imaging and Communications in Medicine (DICOM): Greyscale Standard Display Function (GSDF) [99]-[101].

After reading both mammogram images of a case, the participants had to answer the following question: "refer or not refer?" by focusing their gaze on one of these two options on the screen. Fig. 6.2 illustrates a sequence of the test configuration.



(a) (b)

(c)

Fig. 6.2: Illustration of the experimental procedure: (a) represents the MLO view of a left breast, (b) represents the MLO view of the corresponding right breast, and (c) represents the question asked to the participants after reading.

The experiments were carried out in the University Hospitals KU Leuven. The experiment was conducted in a radiology reading room environment, and the viewing distance was maintained around 60 cm. The eye movements of the participants were recorded using a SensoMotoric Instrument (SMI) Red-m eye-tracking system at a sampling rate of 250 Hz.

6.2.3 Participants

A total of eight participants were involved in the experiment, all having normal or corrected-to-normal vision. Amongst the participants, there were three expert radiologists, having eight, fifteen and twenty years of experience in mammography reading. They are hereafter referred to as R1, R2, and R3, respectively. Note that the sample size used (i.e., three experienced breast radiologists) is considered adequate due to the high degree of consistency among expert readers [18]. The other participants consisted of three trainee radiologists, referred to as T1, T2, and T3, and two physicists, having three years of experience, referred to as P1 and P2.

6.3 Experimental results

6.3.1 Gaze duration

6.3.1.1 Ground truth

Gaze information (i.e., number of fixations for each stimulus, their coordinates, and their duration) was extracted from the raw eye-tracking data. Fig. 6.3 shows the mean duration of fixations recorded over all stimuli for each expert radiologist, i.e., R1, R2, and R3. First, we analyse the intra-observer variation, i.e., the amount of variation one observer behaves in terms of the fixation duration. This can be revealed by the 95% confidence interval: [295 ms, 320 ms] for R1, [280 ms, 304 ms] for R2, and [284 ms, 304 ms] for R3.

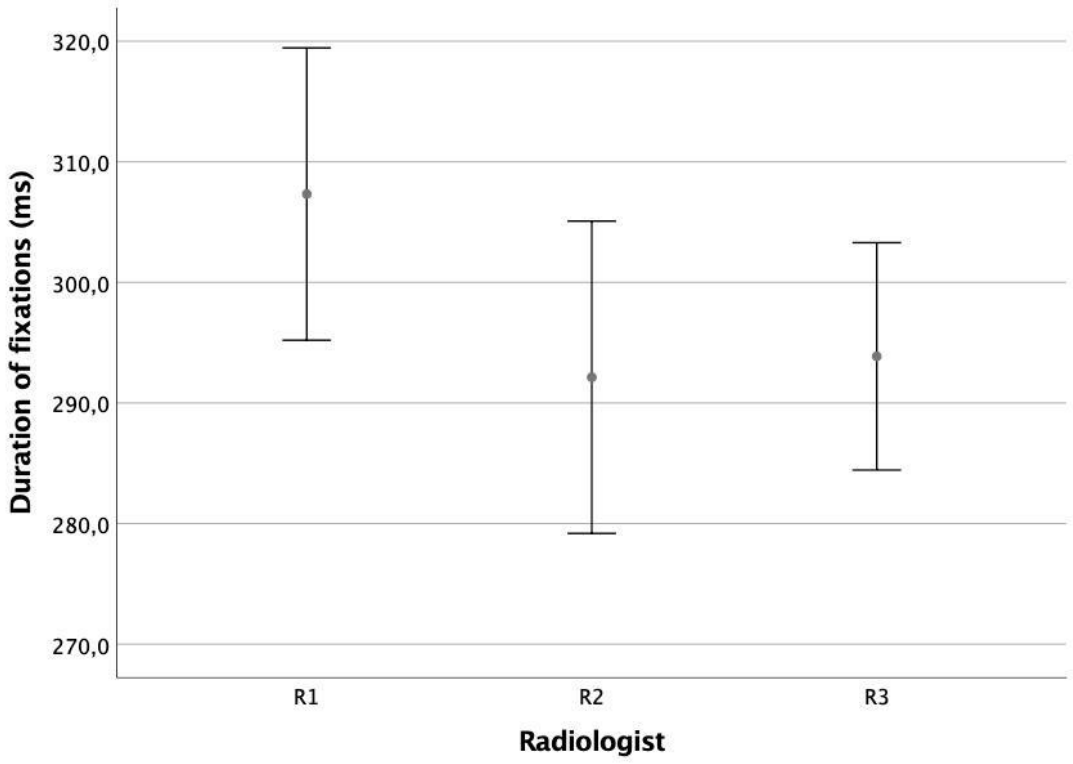


Fig. 6.3: Illustration of the mean fixation duration for each expert radiologist, averaged over all fixations recorded for all test stimuli. Error bars indicate a 95% confidence interval.

It can be seen from Fig. 6.3 that the mean fixation duration of the three expert radiologists is similar. This tendency is further statistically analysed using a one-way ANOVA, where the fixation duration is selected as the dependent variable, and the radiologist as independent variable. Note the one-way ANOVA assumptions are not

violated as the dependent variable is tested to be normally distributed. The results of the ANOVA are summarised in Table 6.1, where the F-statistic (i.e., F) and its associated degrees of freedom (i.e., df) and significance (i.e., p-value) are included.

Table 6.1: Results of the onbe-way ANOVA to evaluate the effect of "Radiologist" on the fixation duration.

Factor	df	F	p-value
Radiologist	2	1.97	0.140

The results show that there is no statistically significant difference between the radiologists in terms of duration of fixations (i.e., p>0.05). This consistency in gaze behaviour among expert radiologists may be explained by the fact that all observers have substantial experience in mammography screening and they have developed a consistent viewing strategy. The post-hoc test reveals the following order in fixation duration, again with no significant difference between the radiologists (note that underlined entries are not significantly different from each other):

<u>R2 (<Duration> = 292 ms) < R3 (<Duration> = 294 ms) < R1 (<Duration> = 307 ms)</u>.

Considering the homogeneity of expert radiologists regarding their duration of fixations, we could now formulate a "gold standard" R of the average duration of fixations (representing the behaviour of an average expert radiologist), as follows:

$$\mu = \frac{1}{3}\sum_{i=1}^{3} \mu_i$$

with μ_i for a radiologist i is defined as:

$$\mu_i = \frac{1}{n}\sum_{j=1}^{n} x_j$$

where n is the total number of fixations recorded over the 196 stimuli used in our study and x_j is the duration of the fixation j. We will compare the mean fixation duration of trainee radiologists and physicists against this "gold standard" and investigate whether gaze duration can be used as a metric to distinguish different groups of readers.

6.3.1.2 Trainee radiologists

Gaze information was similarly extracted for the three trainee radiologists. According to the literature, mammography readers with different degrees of experience can be characterised by their gaze duration [5]. The duration of fixations of each student was thus further compared with the average expert radiologist. Fig. 6.4 represents the average fixation duration of T1, T2, and T3 when compared with the "gold standard" gaze duration of R. The intra-observer variation is revealed by the 95% confidence interval: [271 ms, 290 ms] for T1, [263 ms, 279 ms] for T2, and [165 ms, 176 ms] for T3.

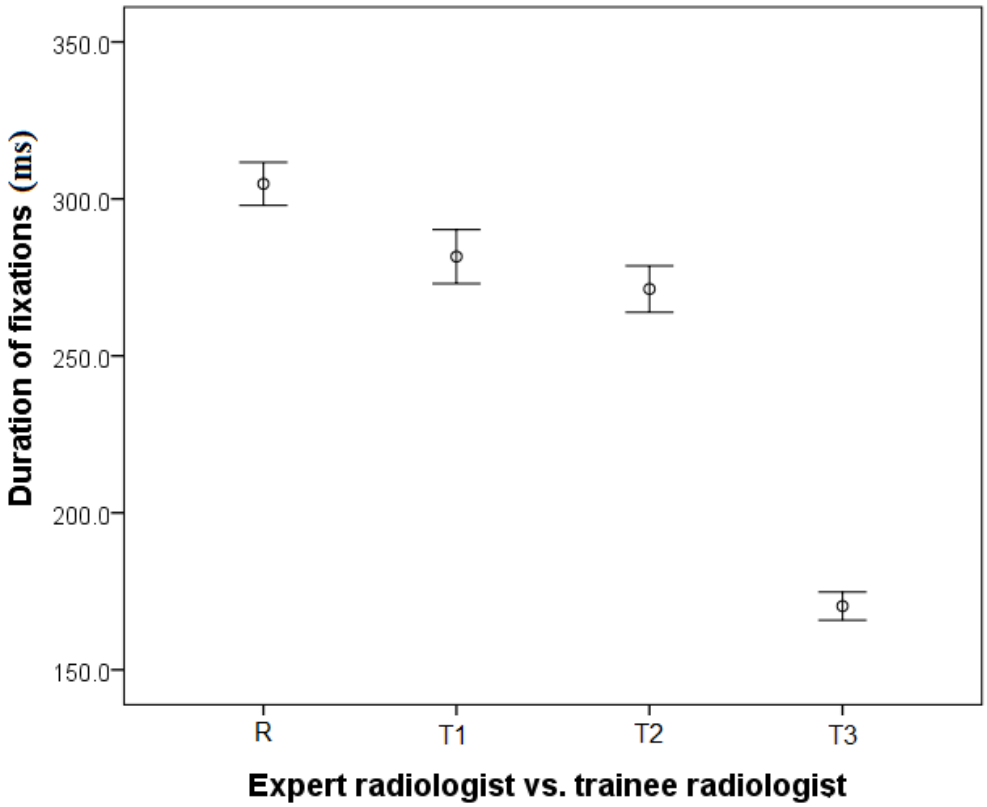


Fig. 6.4: Illustration of the mean fixation duration of the average expert radiologist R and of the trainee radiologists T1, T2 and T3, averaged over all fixations recorded for all test stimuli. Error bars indicate a 95% confidence interval.

A statistical significance test is performed with the duration of fixations as dependent variable and the participant, i.e., average expert radiologist vs. trainee radiologist, as independent variable. The test for the assumption of normality indicates that the samples are normally distributed, therefore independent samples *t*-test are conducted

for three pairwise comparisons and the results are summarised in Table 6.2. In each case, the results (i.e., p-value<0.05) indicate that there is a statistically significant difference between the average expert radiologist and T1, T2, and T3, respectively.

Table 6.2: Results of the t-test to evaluate the difference between each trainee radiologist (T1, T2, and T3) and the average expert radiologist (R)

Trainee radiologist	t	p-value
T1	3.65	<0.001
T2	5.53	<0.001
T3	25.70	<0.001

In addition, we can notice that trainee radiologists had shorter duration of fixations than the average expert radiologist, as revealed by the post-hoc test as follows (note that commonly underlined entries are not significantly different from each other, with the commonly used 5% threshold):

T3 (<Duration> = 170 ms) < <u>T2 (<Duration> = 271 ms) < T1 (<Duration> = 282 ms)</u> < R (<Duration> = 305 ms).

6.3.1.3 Physicists

A similar analysis was carried out to compare the physicists with the average expert radiologist. Fig. 6.5 illustrates the average fixation duration of P1 and P2 when compared to the "gold standard" gaze duration of R. The intra-observer variation is given by the 95% confidence interval: [361 ms, 390 ms] for P1, and [325 ms, 348 ms] for P2.

Table 6.3 gives the results of the independent samples *t*-test (note samples are tested to be normally distributed) for two pairwise comparisons, to compare the gaze behaviour of expert radiologist and physicists. There is a significant difference between P1 and R (i.e., p-value<0.05), and between P2 and R (i.e., p-value<0.05).

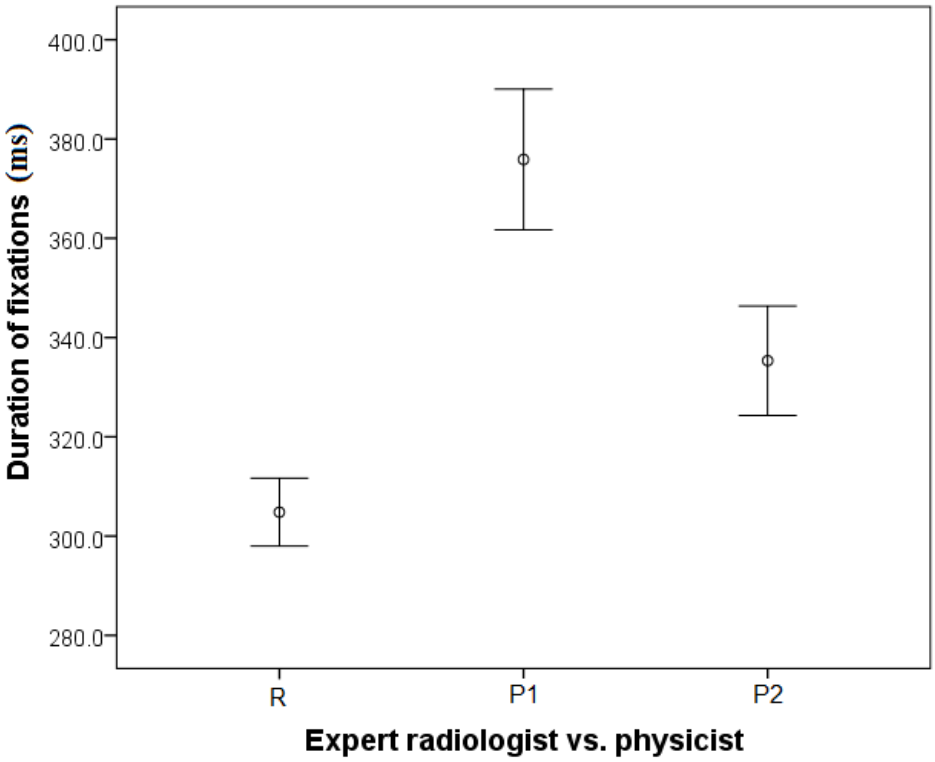


Fig. 6.5: Illustration of the mean fixation duration of the average expert radiologist R and of the physicists P1 and P2, averaged over all fixations recorded for all test stimuli. Error bars indicate a 95% confidence interval.

Table 6.3: Results of the t-test to evaluate the difference between each physicist (P1 and P2) and the average expert radiologist (R)

Trainee radiologist	t	p-value
P1	9.41	<0.001
P2	4.34	<0.001

In general, the duration of fixations of the physicists is higher than that of radiologists: R (<Duration> = 305 ms) < P2 (<Duration> = 335 ms) < P1 (<Duration> = 376 ms).

This observed difference could be explained by the fact that physicists do not perform detection and recognition tasks and their viewing behaviour may contain more “look” patterns (i.e., long fixation duration) rather than “scan” patterns (i.e., short fixation duration).

6.3.1.4 Summary

Fig. 6.6 summarises the duration of fixations for each reader group, i.e., expert radiologists, trainee radiologists, and physicists.

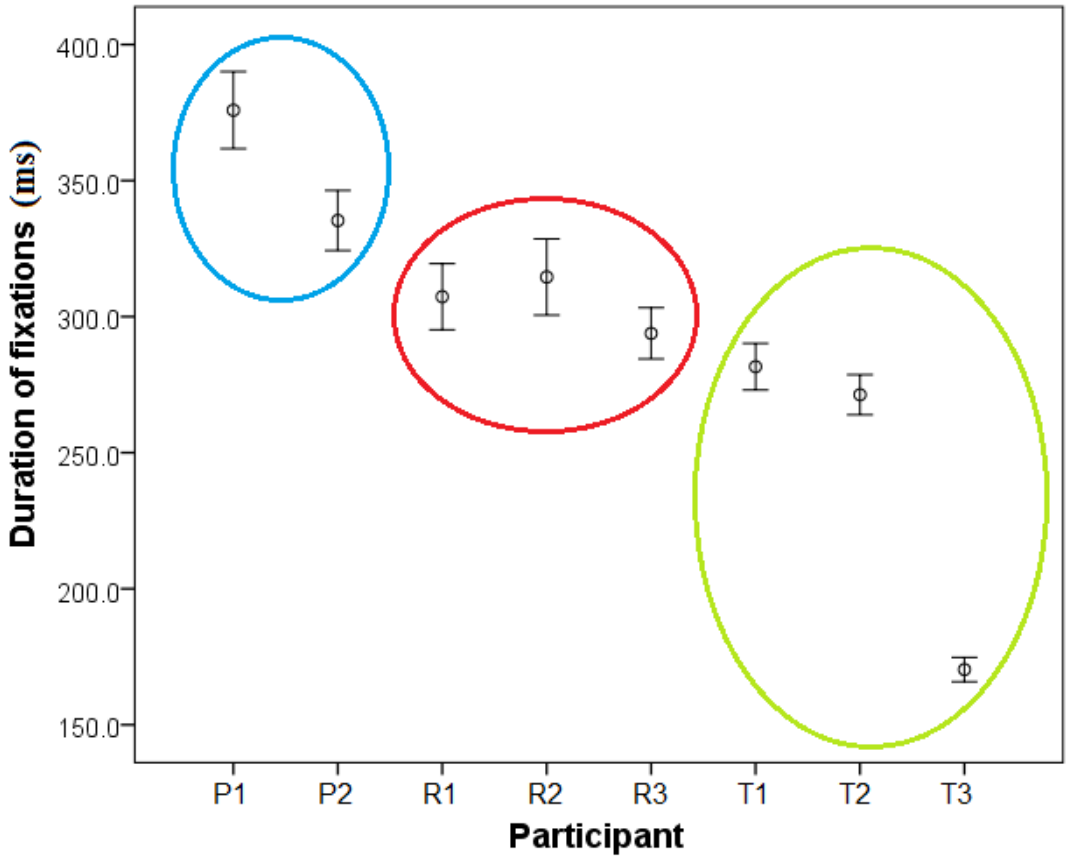


Fig. 6.6: Illustration of the mean fixation duration of the expert radiologists R1, R2 and R3 (in red), the trainee radiologists T1, T2 and T3 (in green) and the physicists P1 and P2 (in blue), averaged over all fixations recorded for all test stimuli. Error bars indicate a 95% confidence interval.

It can be seen that the three groups of readers have different viewing behaviour in terms of duration of fixations. Physicists have a significantly higher dwell time than expert radiologists; and trainee radiologists have a significantly lower dwell time than expert radiologists. The differences in fixation duration intrinsically reflect the effects of expertise and experience on image reading, and thus could be potentially used to characterise the behaviour of mammogram readers.

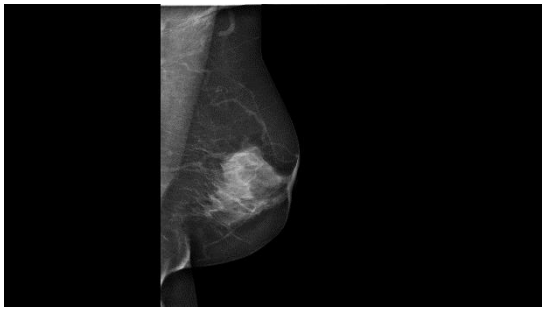
6.3.2 Fixation deployment

Fig. 6.7 represents the saliency maps created from our eye-tracking data for four sample stimuli, for the different groups of participants (i.e., expert radiologists, students, and physicists).

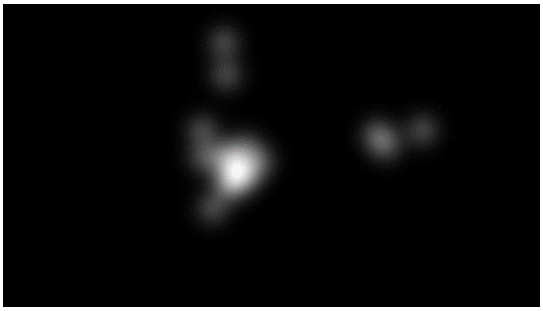
It can be seen from Fig. 6.7 that expert and trainee radiologists' gaze patterns are more concentrated than physicists' gaze patterns. This may be explained by the fact that radiologists (both experts and trainees) aim to make a diagnosis using specific image features. Furthermore, the figure tends to show that trainee radiologists' gaze patterns are rather similar to the expert radiologists (at least for the most focused (i.e., the brightest) areas in the saliency map), which could be interpreted as a positive result of their radiology training and learning.

The similarity between the maps of each group (i.e., expert radiologists, trainee radiologists, and physicists) was quantified using the Pearson Correlation Coefficient (CC), the Normalised Scanpath Saliency (NSS), and the Area Under ROC Curve (AUC) [115], introduced in Chapter 5.

Fig. 6.8 represents the similarity measures of expert radiologists vs. trainee radiologists, and expert radiologists vs. physicists, averaged over all stimuli in our database. In general, the CC, NSS, and AUC values show that the saliency of trainees and physicists are different from the saliency of experts, e.g., the CC values are around 0.7 (out of a maximum of 1) and the AUC values are around 0.6 (out of a maximum of 1).



(a)



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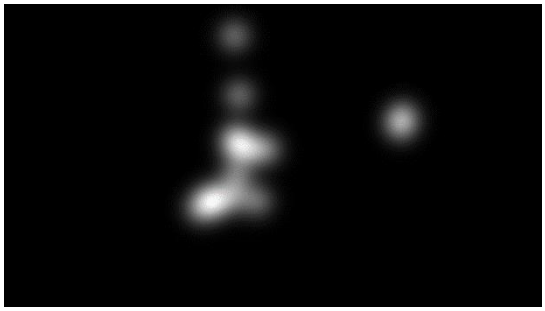

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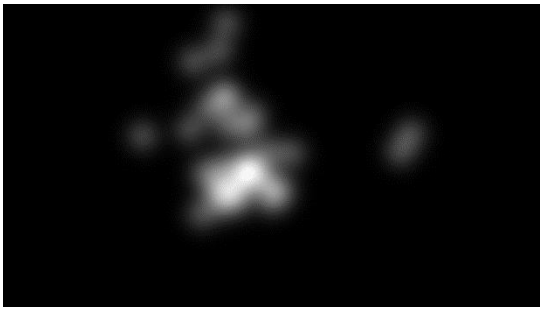

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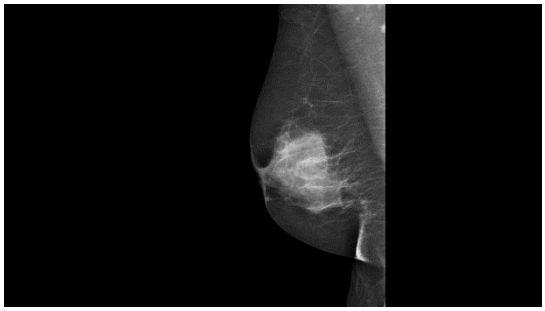

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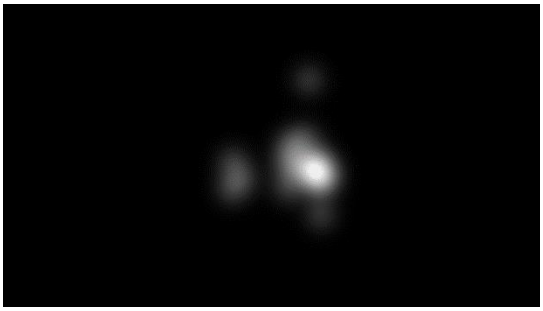

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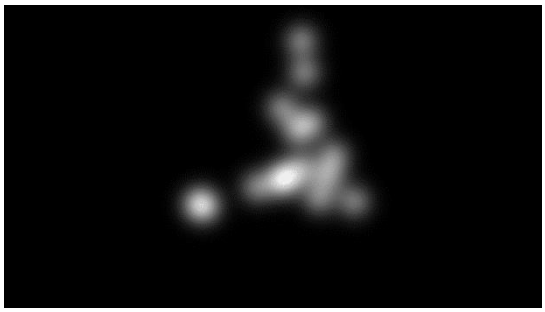

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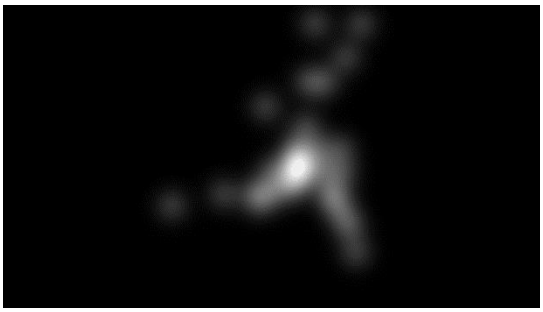

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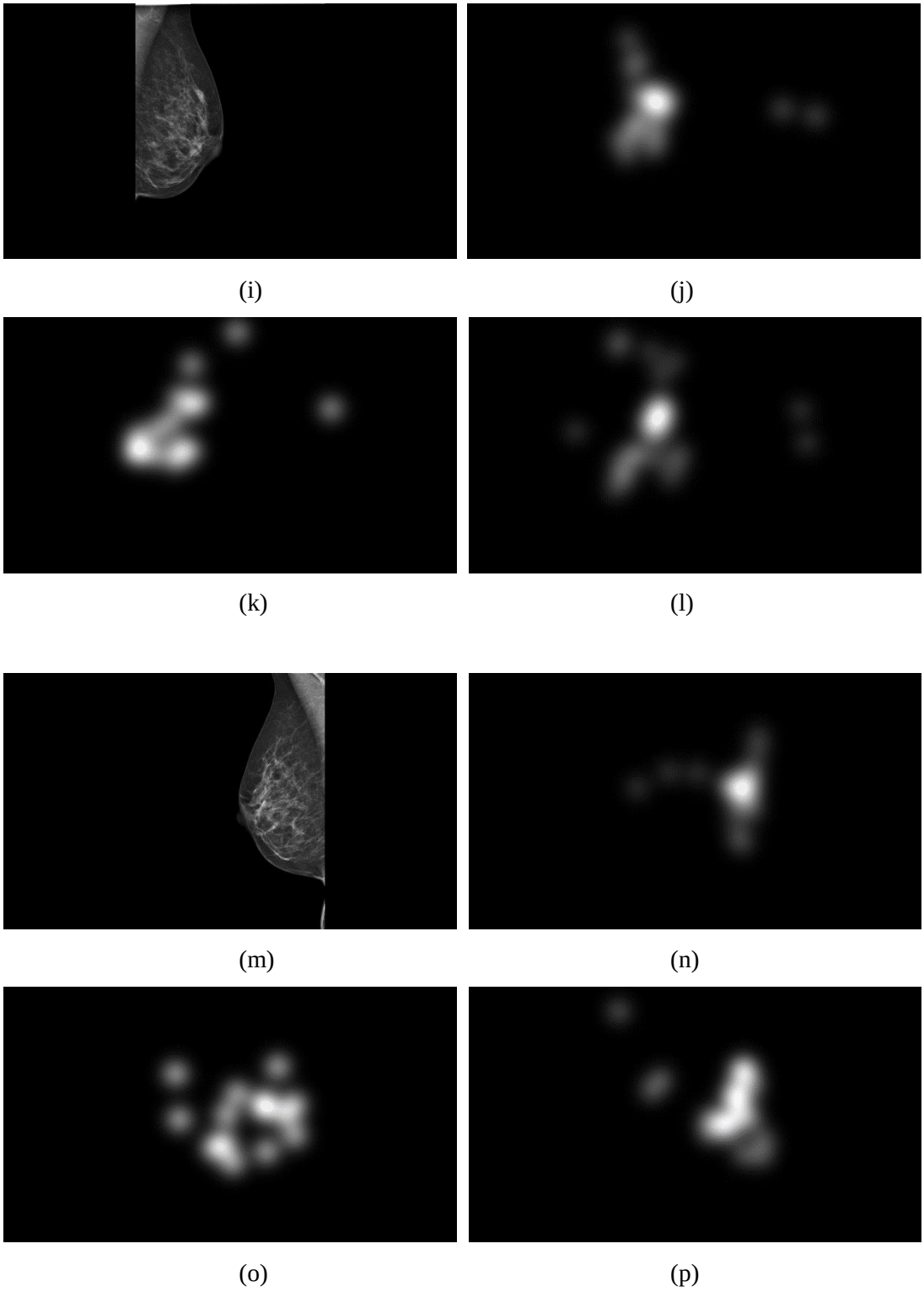


Fig. 6.7: Illustration of the saliency maps constructed for four sample stimuli used in our experiment: (a), (e), (i), and (m) represent the original stimuli; (b), (f), (j), and (n) represent the saliency maps of the expert radiologists; (c), (g), (k), and (o) represent the saliency maps of the physicists, and (d), (h), (l), and (p) represent the saliency maps of the trainee radiologists. The brighter the regions, the higher the saliency.

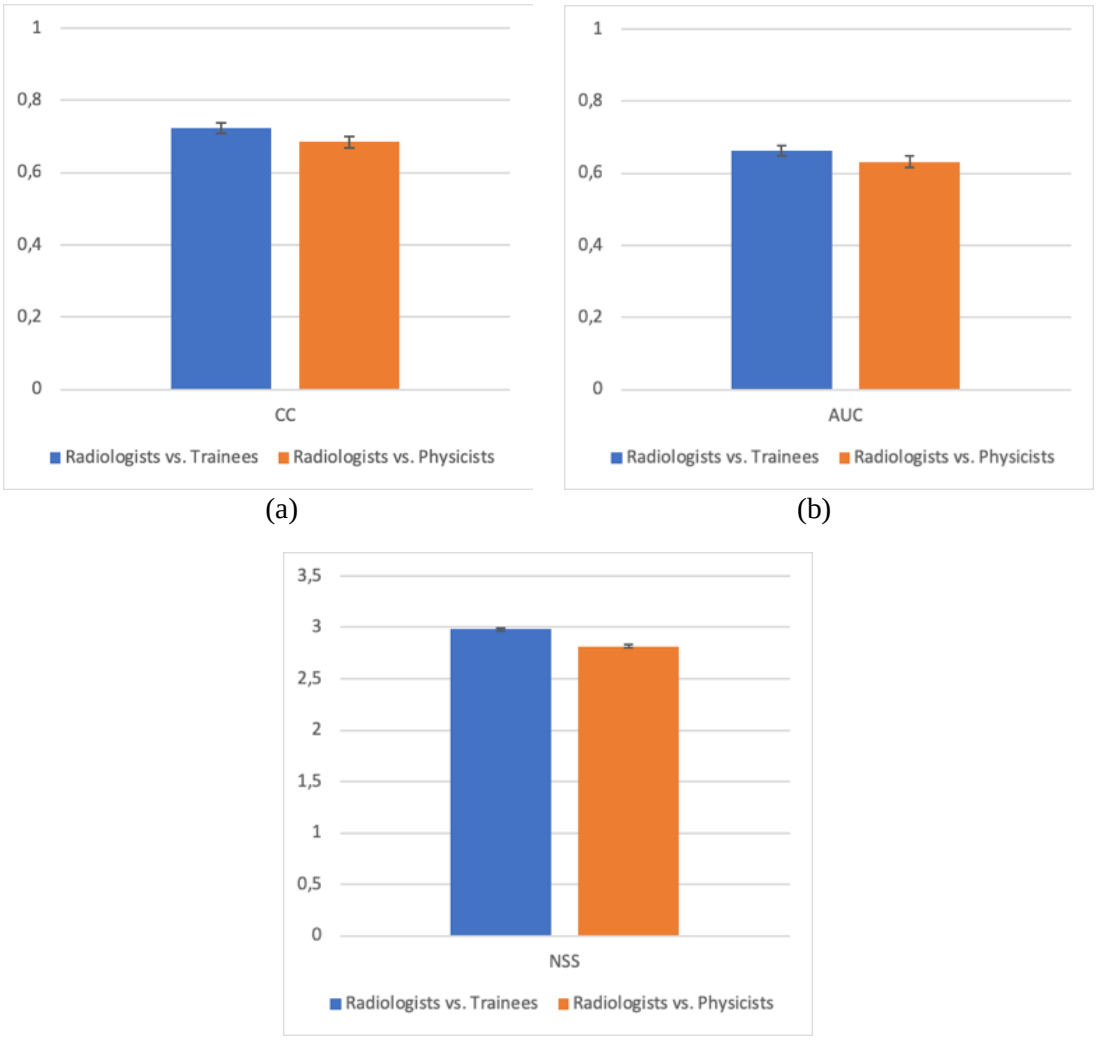


Fig. 6.8: Illustration of the similarity measures between expert radiologists vs. trainees and physicists, averaged over the 196 stimuli using the CC (a), AUC (b), and NSS (c) metrics.

Interestingly, however, it can be seen from Fig. 6.8 that the trainees seemed to perform better than the physicists, as the CC, AUC, and NSS values of trainees are higher than physicists. This observation was further analysed using hypothesis testing (i.e., an independent samples *t*-test is conducted as samples are tested to be normally distributed) and the results are presented in Table 6.4.

The results of the *t*-tests (i.e., $p<0.05$ in all cases) show that the trainee radiologists performed significantly better than the physicists in terms of their similarity to expert radiologists in reading images.

Table 6.4: Results of the t-test to evaluate the difference between the trainee radiologists T and the physicists P in terms of their similarity with the expert radiologists for each of the three metrics (i.e., CC, NSS, and AUC)

Metric	t	p-value
CC (T vs. P)	3.70	<0.001
NSS (T vs. P)	2.91	0.002
AUC (T vs. P)	5.62	<0.001

6.3.3 Analysis of saccadic features

Eye movements are mainly composed of fixations and saccades. A saccade is a quick, simultaneous movement between two fixations. The sequence of fixations and saccades represents a visual scanpath of a human observer, which gives useful information about how an observer moves their gaze in a visual field [117].
Now, we analyse two important saccadic features, saccade amplitude and saccade orientation, and evaluate how these features differ for different reader groups.

The saccade amplitude, expressed in degree of visual angle, corresponds to the Euclidian distance between two consecutive fixations [118]. Fig. 6.9 illustrates the distribution of saccade amplitudes of the expert radiologists, trainee radiologists, and physicists. It can be seen from Fig. 6.9 that three reader groups show different eye movement patterns, while within each group, observers exhibit similar saccadic patterns. Furthermore, saccade amplitudes are shorter for the expert radiologists than for the trainee radiologists; and saccade amplitudes are shorter for the trainee radiologists than for the physicists.

The above observations were further statistically analysed using hypothesis testing. A one-way ANOVA (note the dependent variable is tested to be normally distributed) is performed to compare the saccade amplitudes between the three groups, i.e., expert radiologists, trainee radiologists, and physicists. The results of the ANOVA are illustrated in Table 5, and demonstrate a significant difference between the three reader groups (i.e., $p<0.05$).

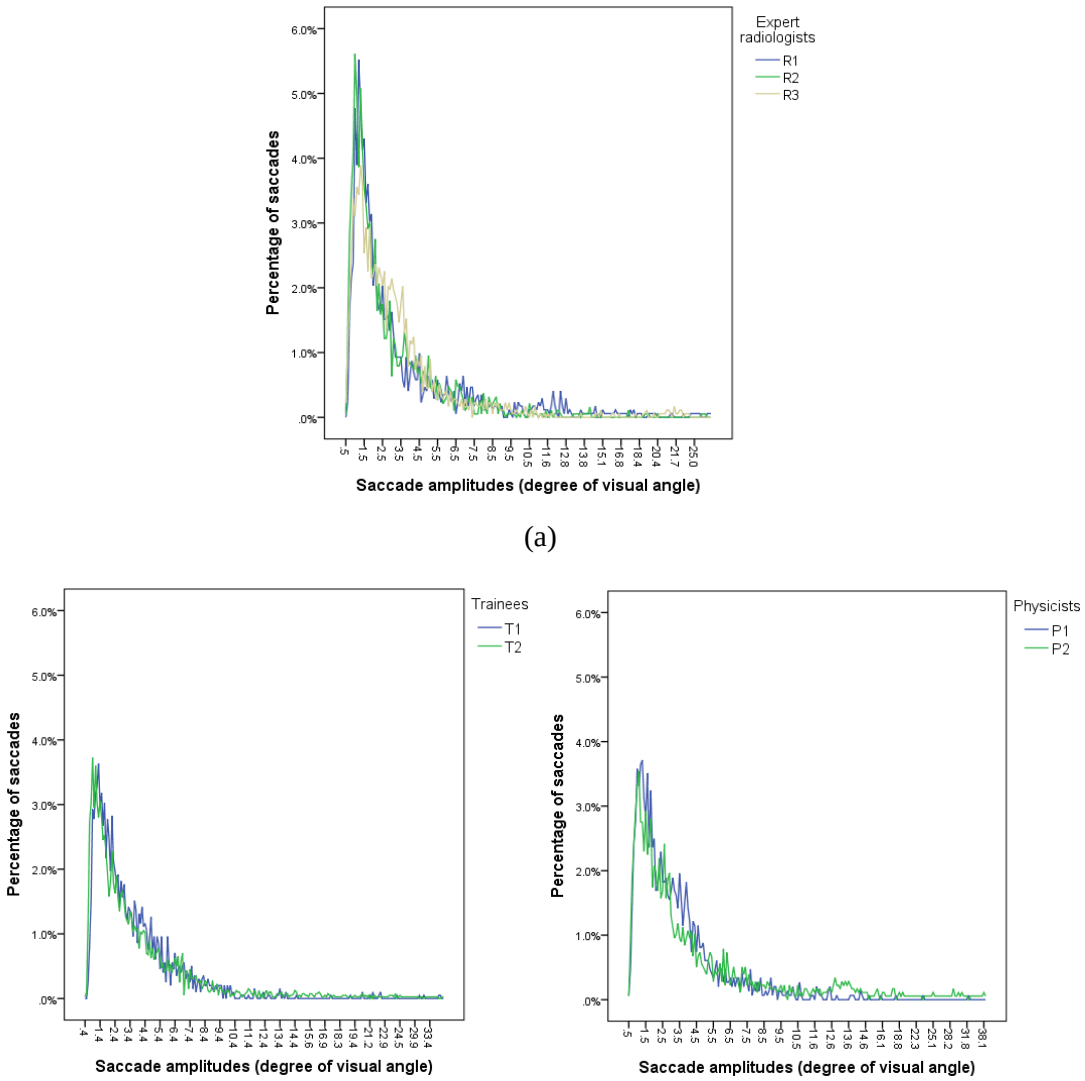
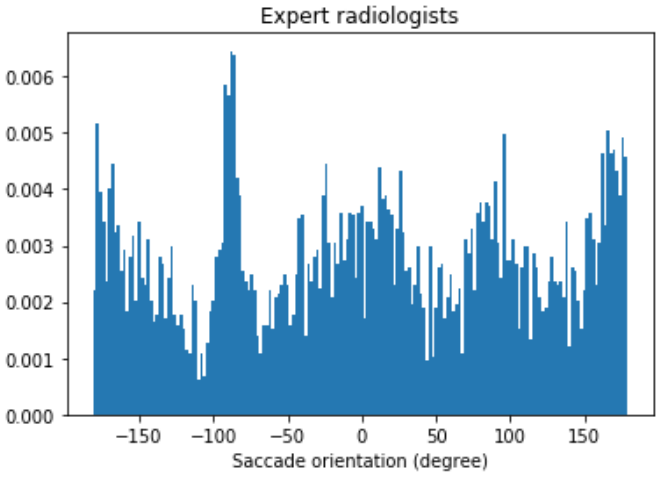


Fig. 6.9: Illustration of the distribution of saccade amplitudes for each observer group: (a) expert radiologists, (b) trainee radiologists, and (c) physicists.

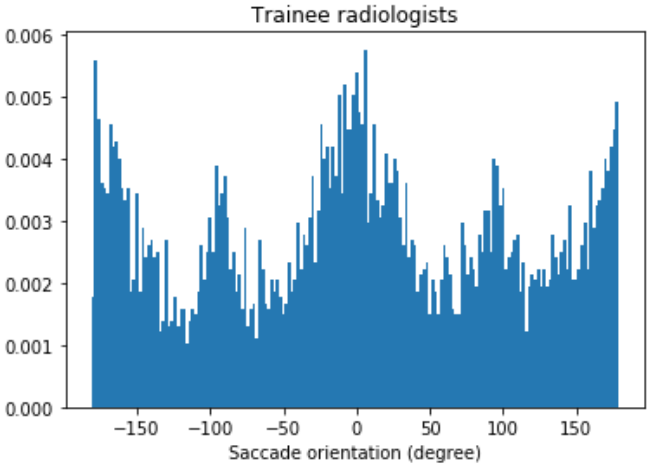
Table 6.5: Results of the one-way ANOVA to evaluate the differences between the three reader groups in terms of the saccade amplitudes.

Factor	df	F	p-value
Reader group	2	53.58	<0.001

The saccade orientation, expressed in degree, corresponds to the angle between two consecutive fixation points [118]. Fig. 6.10 illustrates the distribution of the saccade orientations of expert radiologists, trainee radiologists, and physicists.



(a)



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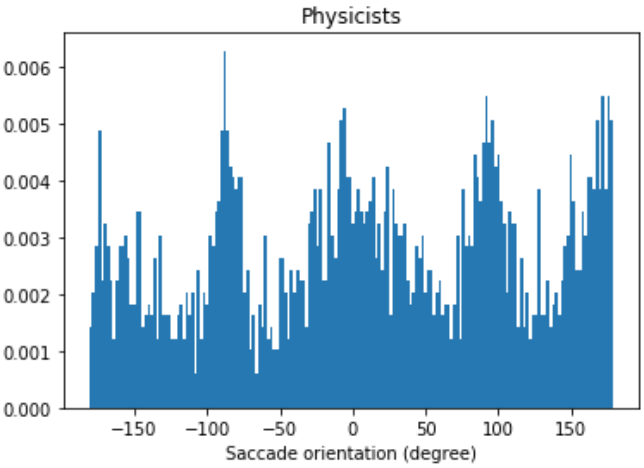

(c)

Fig. 6.10: Illustration of the distribution of saccade orientations for each observer group: (a) expert radiologists, (b) trainee radiologists, and (c) physicists.

It can be seen from the figure that the three observer groups present different orientation distributions. For instance, expert radiologists' distribution of saccade orientations shows a sharp peak around -100 degrees; the distribution of trainee radiologists' saccade orientations presents a gradual peak around 0 degree; and physicists' distribution contains multiple gradual peaks.

In summary, the results suggest that saccadic features, including saccade amplitudes and orientations are strongly dependent on observers' expertise and experience in image reading. Again, these saccadic features can be used to characterise the gaze behaviour of mammogram readers.

6.4 Main findings and contributions

In this chapter, we studied the impact of different medical specialties (i.e., radiologist versus physicist) and levels of experiences (i.e., expert versus trainee radiologist) on the human perceptual behaviour while interpreting medio-lateral oblique mammogram views through a large-scale eye-tracking experiment.

The eye-tracking data, collected from expert radiologists, trainees, and physicists, were analysed using different – yet complementary – metrics, i.e., gaze duration, gaze deployment, and saccadic features. The results showed that gaze metrics can be used to quantify to what extent trainees or physicists are in agreement with experts in terms of where to focus in images. In general, physicists have a significantly higher dwell time than experts, and trainee radiologists have a significantly lower dwell time than experts. The physicists gaze patterns were more dispersed than that of the radiologists, whereas the trainees showed similar patterns to that of the radiologists. The trainee radiologists thus performed better than the physicists.

Chapter 7:
Conclusions and discussion

This thesis aims to investigate the perceptual behaviour of medical professionals when interacting with medical visual content (i.e., images or videos) in various contexts of applications. Existing issues in medical image perception have been identified in the previous chapters, and subjective experiments were designed and conducted to approach these problems. Statistical evaluations were performed to reveal and quantify the viewing behaviour of observers.

Overall, our research questions were answered by experimental results, and research objectives were fulfilled. In this final chapter, the main conclusions drawn are first summarised. Afterwards, several points in close relation to this thesis are discussed, as well as some possible research directions which could be considered in future studies.

7.1 Study of perceived visual quality

With the advances in medical imaging technologies, as well as in information and communication technologies, health professionals are nowadays viewing medical imaging content in diverse environments. Furthermore, their quality of experience might be affected depending on their medical specialty, their degree of experience, and the clinical context they are facing. To optimise clinical practice, it is thus of fundamental importance to understand how medical experts perceive the visual quality of medical images and videos.

In this thesis, we first conducted subjective experiments in the context of telemedicine with expert surgeons. Based on the qualitative results provided by semi-structured interviews, a subjective video quality assessment experiment was designed and carried out. Quantitative results showed the strong impact of the contextual factor, i.e., medical procedure and video content, on the perceived quality. Similarly, the system factor, i.e., video compression scheme, bit rate, frame rate, and packet loss rate, also demonstrated its impact on the perceived quality.

Secondly, a psychophysical study was undertaken to evaluate how specialty settings affect the perceived quality. Via a dedicated subjective experiment, we investigated whether and to what extent radiologists and sonographers, two specialties working together but having distinct backgrounds, differently perceive the quality of compressed ultrasound videos. Toward this goal, videos of different ultrasound exams were distorted with various compression schemes and ratios. The statistical analyses showed that the way video quality changes with content and compression configuration tends to be consistent for radiologists and sonographers, however, the results demonstrated that sonographers are more bothered by the distortions than the radiologists for highly compressed stimuli.

7.2 Study of human visual attention

Another unintrusive way to explore medical experts' perception of medical visual information is by using eye-tracking technology, which allows analysing the gaze behaviour of human subjects. We first conducted a new eye-tracking study where a large-scale database of two-view mammograms was assessed by eight expert radiologists. The analysis of their eye movements showed how attention is allocated to the medio-lateral oblique view versus the cranio-caudal view, using the fixation duration and fixation deployment metrics. Furthermore, we demonstrated that existing computational models of visual attention fail to represent the "ground truth" data obtained from the radiologists.

Finally, we conducted another eye-tracking study where a large number of medio-lateral oblique view mammograms was assessed by expert radiologists, trainee radiologists, and physicists. Statistical analyses showed the consistency between the experts in terms of gaze duration, as well as the differences between trainee radiologists and experts, and between physicists and experts. An evaluation of the fixation deployment reinforced this conclusion. The trainee radiologists performed better than the physicists in terms of their similarity with the radiologists' gaze behaviour. Knowledge on how expert radiologists search mammograms could be used to improve educational practice.

7.3 Future work

7.3.1 Technological complexity

Medical imaging is composed of a wide range of areas of application, including, but not limited to: radiography, ultrasonography, and endoscopy. Each area presents diverse set of characteristics in imaging, including 2D or 3D content, images or videos, and content in colour or in black and white.

Due to the technological complexity of medical imaging, distinct artifacts may be induced in the medical visual signals in data acquisition or image reconstruction. In this thesis, only a limited sample of medical imaging modalities (i.e., open and laparoscopic surgery, hepatic ultrasound, and mammograms) and artifacts were investigated. Exploring more modalities would be highly beneficial for medical image perception research.

7.3.2 User community

The fact that different health practitioners work with the same set of medical content was raised in the previous chapters, and this can happen in the same hospital or environment. Even though they have different backgrounds and received different specialised training, all the practitioners aim to care for their patients. Due to their different experience and expertise, these users present distinct needs and perceptual behaviour when viewing medical imaging data.

In this thesis, we studied different health professionals, i.e., surgeons, radiologists, sonographers, and physicists. This list already covers a broad range of professions, however, there are yet more to be added, including generalist practitioners and nurses for instance. Widening the field of medical professions will help research by offering a better comprehension of the problem.

7.3.3 Demographic complexity

In this thesis, we worked closely with British and French health professionals, i.e., from developed countries (MEDCs), and thus with up-to-date technologies. But what about developing countries (LEDCs) in Asia, Africa, and Latin America with lower economic levels, and therefore with fewer state-of-the-art resources?

There has been an increasing demand for telemedicine in developing economies, where access to and delivery of timely and high-quality healthcare in resource-poor settings remain very limited. For example, in August 2014, the National Health and Family Planning Commission of the People's Republic of China (NHFPC) issued comprehensive guidelines on telemedicine services to push forward the deployment.

It would be highly beneficial to develop medical image perception research with developing countries to improve their clinical practice and health conditions.

7.3.4 Objective approaches

In this thesis, a subjective approach was developed for video quality assessment, i.e., experiments with human subjects (medical professionals in our case). It should be noted that evaluation with subjective experimentation is intrinsically time-consuming, and thus limited with respect to the amount of test stimuli and the number of available medical experts. Adding more experimental data to our evaluation would be highly beneficial, especially in terms of adding confidence to the generalisability of the conclusions.

A more realistic and practical way to assess the perceived quality of images and videos is to use computational models, i.e., image and video quality metrics. To date, very little objective quality assessment has been done for the development of medical images and videos. Some recommended compression ratios have been published in the literature, but they are based on subjective scores given by radiologists assessing a small number of images.

Widely recognised models developed for natural images and videos, such as PSNR (peak signal-to-noise ratio) and SSIM (structural similarity index) [119], were applied in the literature for the assessment of image and video quality in medical imaging. The correlation between the predictions of these models is very poor. These results suggest that there is plenty of headroom for further improvement in objective quality assessment in the particular context of medical imaging. Such new objective methods would benefit not only the acquisition, storage, and presentation of medical images, but also the development of new medical imaging methods which could offer better image quality.

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Appendix

Appendix 1: Raw data, controlled experiment, open surgery

Content	Surgeon	128 kbps	256 kbps	350 kbps	512 kbps	1000 kbps
1	1	0	2	8	8	8
1	2	0	2	5	8	9
1	3	0	2	3	8	8
1	4	1	4	5	7	10
2	1	0	3	7	8	7
2	2	1	4	5	7	8
2	3	0	1	4	5	6
2	4	2	6	7	8	9
3	1	0	2	4	7	8
3	2	0	2	4	8	8
3	3	0	0	2	7	8
3	4	3	7	8	9	9
4	1	0	7	8	9	9
4	2	1	4	6	8	9
4	3	0	4	8	9	9
4	4	2	6	7	8	10

Content	Surgeon	15 fps	PL 1%	PL 3%
1	1	8	7	7
1	2	8	5	3
1	3	8	5	2
1	4	8	9	2
2	1	8	7	6
2	2	7	5	1
2	3	6	5	1
2	4	9	8	6
3	1	7	5	4
3	2	8	3	3
3	3	8	1	1
3	4	10	7	3
4	1	8	8	6
4	2	7	5	2
4	3	9	5	2
4	4	7	8	0

Appendix 2: Raw data, controlled experiment, laparoscopy

Content	Surgeon	128 kbps	256 kbps	350 kbps	512 kbps	1000 kbps
1	1	3	6	3	7	7
1	2	4	3	6	7	8
1	3	1	4	3	6	7
1	4	3	6	7	7	8
2	1	3	2	4	6	9
2	2	0	4	5	6	8
2	3	3	3	4	6	7
2	4	5	6	7	8	9
3	1	3	5	5	6	9
3	2	1	5	4	8	8
3	3	1	5	5	9	9
3	4	7	9	9	10	10
4	1	0	3	4	8	9
4	2	0	2	5	7	8
4	3	0	1	5	5	8
4	4	2	8	8	10	10

Content	Surgeon	12.5 fps	PL 1%	PL 3%
1	1	6	6	3
1	2	4	4	5
1	3	5	2	3
1	4	6	7	7
2	1	3	4	2
2	2	5	3	2
2	3	5	6	4
2	4	10	9	5
3	1	5	7	2
3	2	5	5	2
3	3	6	7	6
3	4	9	9	8
4	1	2	7	2
4	2	4	6	2
4	3	3	4	7
4	4	10	9	6

Appendix 3: Raw data, dedicated experiment, open surgery

Content	Surgeon	H.264 256	H.264 384	H.264 512	HEVC 128	HEVC 256	HEVC 384	HEVC 512
1	1	15	40	74	20	50	60	70
1	2	65	80	85	48	80	85	87
1	3	48	85	83	59	78	74	71
1	4	28	82	64	23	37	70	47
1	5	27	76	53	31	48	81	80
1	6	55	45	70	40	60	75	75
1	7	50	65	80	25	70	70	85
1	8	74	82	91	65	76	85	87
2	1	10	20	60	5	45	75	90
2	2	39	65	80	28	85	85	85
2	3	19	47	71	49	41	80	63
2	4	32	56	70	26	63	79	66
2	5	12	44	75	19	35	89	88
2	6	31	75	51	11	61	70	58
2	7	40	65	75	50	70	85	80
2	8	56	88	60	51	68	78	76
3	1	5	40	50	10	70	80	100
3	2	15	63	76	32	77	90	90
3	3	48	64	72	61	89	56	76
3	4	33	48	63	28	65	55	90
3	5	26	66	81	46	68	82	81
3	6	40	74	70	35	80	76	80
3	7	30	55	60	45	75	80	70
3	8	72	87	86	81	85	88	84
4	1	5	10	30	0	15	50	80
4	2	12	51	92	18	94	80	81
4	3	0	47	37	4	12	57	84
4	4	27	40	88	27	77	84	88
4	5	14	10	76	0	65	50	60
4	6	10	80	70	35	75	80	82
4	7	47	70	75	10	70	86	90
4	8	35	51	67	10	58	77	73

Appendix 4: Raw data, radiologists

Content	Radiologist	H.264 512	H.264 1000	H.264 1500	HEVC 384	HEVC 512	HEVC 768	HEVC 1000
1	1	62	75	75	27	48	75	83
1	2	50	65	75	60	55	60	70
1	3	35	65	95	60	60	35	80
1	4	63	80	81	63	80	83	81
1	5	32	48	48	44	36	49	44
1	6	48	33	77	29	70	41	58
1	7	58	62	78	73	77	85	98
1	8	70	78	90	83	85	73	82
2	1	19	34	40	18	35	51	53
2	2	40	45	35	20	40	52	55
2	3	5	50	65	5	5	50	65
2	4	60	72	73	64	68	66	69
2	5	20	70	55	6	33	48	65
2	6	55	48	55	37	29	70	74
2	7	30	44	48	38	45	53	55
2	8	46	64	67	32	38	56	54
3	1	13	35	45	13	25	50	70
3	2	25	45	65	40	50	60	70
3	3	10	55	60	20	20	60	55
3	4	50	65	79	56	58	63	59
3	5	48	76	69	66	54	53	59
3	6	29	73	63	37	34	39	65
3	7	40	69	69	44	74	50	58
3	8	37	58	85	51	73	67	71
4	1	82	92	91	58	92	91	91
4	2	35	60	60	35	40	45	50
4	3	15	35	90	5	15	30	60
4	4	56	71	55	50	69	61	69
4	5	84	85	91	72	85	89	85
4	6	51	79	82	48	94	88	55
4	7	37	46	69	29	48	56	57
4	8	53	62	86	42	57	76	91

Appendix 5: Raw data, sonographers

Content	Sonographer	H.264 512	H.264 1000	H.264 1500	HEVC 384	HEVC 512	HEVC 768	HEVC 1000
1	1	85	80	90	40	45	85	80
1	2	58	60	80	39	87	50	75
1	3	50	75	80	40	75	80	80
1	4	45	70	60	50	80	75	95
1	5	90	85	85	80	85	85	90
1	6	50	80	80	50	80	80	80
1	7	80	80	60	45	80	55	80
1	8	50	50	50	45	50	45	50
1	9	50	85	90	25	90	85	85
2	1	30	60	70	25	45	50	65
2	2	10	42	24	0	17	27	50
2	3	10	60	70	10	15	50	75
2	4	4	40	45	5	35	35	25
2	5	40	70	70	50	50	55	70
2	6	25	50	70	30	50	40	50
2	7	25	60	70	20	45	30	55
2	8	25	85	43	20	50	50	75
2	9	5	25	25	1	25	25	25
3	1	50	60	70	25	75	80	75
3	2	30	80	80	25	30	65	75
3	3	10	65	75	10	60	75	65
3	4	25	50	85	40	50	70	75
3	5	30	75	80	40	75	75	70
3	6	20	70	90	25	60	60	70
3	7	50	80	80	30	80	80	80
3	8	20	80	80	20	75	75	70
3	9	24	80	80	24	60	75	80
4	1	40	60	75	20	60	55	70
4	2	40	45	80	20	50	60	67
4	3	50	60	80	25	55	70	75
4	4	30	65	55	10	35	50	45
4	5	45	65	60	25	50	50	65
4	6	75	70	80	20	50	80	70
4	7	20	60	35	10	25	40	50
4	8	25	90	50	15	25	30	25
4	9	60	80	70	25	70	70	75