Baltic J. Modern Computing, Vol. 3 (2015), No. 4, pp. 248–267

Region-based Annotations for the Medical Images

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Abstract. Annotations facilitate the problems of visual medical information management and data mining. Most of the semantic annotations are targeted for the on-line repositories, and detached from the image data. Instead of using detached annotations, we embed them directly into the reasonably chosen area of the image and use spatial identifiers to bind them with the corresponding regions. The embedding method deals with the different quality requirements of the regions. Two-dimensional QR codes are used as the physical carrier of the annotation, providing the industrial grade for information detection, resilience and error correction capabilities. The annotation is distributed in a series of QR codes for efficient use of the available space. Embedding of annotations into the clinically irrelevant regions of the medical image shows preferable results in the field of informational capacity. The quality of annotated and compressed image is comparable to the image quality loss due to image compression.

Keywords: annotation, region of interest, region of annotation, JPEG 2000, DICOM

1 Introduction

Health care information technologies produce the increasing number of medical images in different imaging modalities, like radiography (CR), computer tomography (CT), magnetic resonance (MR), ultrasound (US), nuclear medicine (NM). Management of medical data volume is complicated, and there is a gap in understanding the visual content of the image. Most of the medical image inspection techniques are based on tacit knowledge of experts. Semantic annotations facilitate the gathering of information from medical experts and can be used to represent the visual knowledge. These data are useful for creation a computer-based assistant, collecting information about the medical inspection process, same as to query and retrieve image from medical record databases. Automated or semi-automated content-based image retrieval (CBIR) systems based on low-level features have demonstrated poor performance when applied to databases with a broad spectrum of imaging modalities, anatomies, and pathologies (Kalpathy-Cramer and Hersh, 2008). The search by particular textual description, or by fusing the results of visual and textual techniques, is more precise compared to the search by the image content. Such method provides better means to organize and search an image database (Kadam et al., 2014).

In this paper we propose the algorithm for annotation of medical images, embedding semantic descriptions directly into the spatially disjointed, insignificant regions of the image, associating them with the region of interest. Quick Response (QR) codes are used as the carriers of structurized information. The annotation technique is tailored to JPEG 2000 image compression standard, saving the transmission time, bandwidth and storage space. Typical usage scenarios are targeted to the off-line usage of medical data and include research work, lectures, conference talks and similar designations when access to the medical information databases is impossible or unacceptable. The annotation method is not a permanent replacement of database records; it is targeted as a tool for pointing out peculiarities of the image. The embedded annotations, encapsulating essential knowledge about the content of medical images, could be used as training data in the machine learning approaches that are employed in the automatic annotation of images (Cruz-Roa et al., 2011).

The novel aspects of our work:

– we propose the basic requirements for region-based medical annotation;
– we use 2D Quick Response (QR) codes as the information carrier, exploiting their positive features, like industry - proven detection methods, error resilience and correction;
– instead of using single QR block, we split the annotation into separate substrings, making the embedding of smaller QR block spatially efficient;
– the recovered substrings are automatically reassembled at the decoding stage, allowing a number of annotations to be placed in the single image;
– the spatial position of the region of interest is included in the structure of an annotation, thus allowing arbitrary placement of every QR block.

The annotating methods for medical images and their drawbacks are presented in subsection 2.1. The quality and level of compression of medical images are discussed in subsection 2.2. Usage requirements for medical images are presented in subsection 3.1. The annotation algorithm is presented in subsection 3.2. Experimental results of the proposed scheme are presented in Section 4 with the conclusions in Section 5.

2 Related works

The annotation methods depend on the objectives of the application area, on the technical resources, on the image type, file format and requirements for annotations. All methods have their advantages and weakness (see Table 1). The annotations differ in their context complexity themselves, and high-level semantic of raster objects can not always be captured precisely using low-level features of images. The similar meaningful regions can have different meaning in medical imaging. There are little intelligent visual tools for sharing the expert's knowledge and for learning from it.

Table 1. Annotation methods

Property	**Type of annotation**		
	dissociated	embedded into the image format	embedded into the image content
Use	On-line	On-line and off-line	
Capacity	Unlimited	Limited	Limited
No quality influence	+	+	—
No extra payload	—	—	+
Independant on file name	—	—	+
Independant on file format	—	—	+

Existing annotations methods of medical imagery and their peculiarities are presented in the following subsection. As our method is based on JPEG 2000 standard, we also discuss the modern quality evaluation methods of compressed annotated medical images of various modalities in the subsequent subsection.

2.1 Annotation methods for the medical images

The majority of articles use eXtensible Markup Language (XML), Web Ontology Language (OWL) and Resource Description Framework (RDF) for the medical image annotations.

The annotation methodology for on-line usage, presented in (Wang et al., 2008), uses XML as platform independent annotation exchange format and the Scalable Vector Graphics (SVG) format to represent the graphical objects — meaningful sub-areas of the image. Introducing two additional formats authors create more payload for transmission and storage of medical images. The content of medical images is frequently described and stored as free-text in an unstructured manner. For solving this problem, OWL was proposed to be used (Channin et al., 2010).

Authors of the project called the Annotation and Image Markup (AIM), have created an information model in Unified Modelling Language (UML) that specifies the information requirements for image annotation and markup in health care (Channin et al., 2010). Their ontology — anatomical structures visualized in images, radiologists observations of the images, spatial regions in images and another meta-data — provides controlled terminology needed to describe image contents when users create annotations on images. The authors of (Channin et al., 2010) claims, there are no standards for image annotation and markup. Therefore, their goal is to develop a mechanism for modeling, capturing and serializing image annotation and markup data that can be adopted as a standard by the medical imaging community.

XML-based annotating methods of medical images are not suitable for all usage cases of annotations. Medical images are stored in disparate systems, both on-line and off-line: in the Web, hospitals, personal repositories, etc. It is hard to share, transfer and store meaningful information and knowledge among researchers, professionals, students, and interested parties using XML-based annotations only. It is related both with the change of image file format or name, and the situations when the connection to an external database or network node is limited to security reasons, connection costs or lack of infrastructure. Thus, when the image content and annotations are separated, handling of annotations is impossible. Furthermore, XML-based annotations create additional payload for image storage and transmission (Table 2).

Table 2. Requirements for the main application areas of information embedding

	Steganography	**Watermarking**	**Media description**
Protects	Message	Cover	Cover and annotation
Aim	Hidden communication	Copyright protection	Information preservation
Goal	Undetectability	High robustness	Information transmission
Message type	The presence of the message is hidden	The presence of the message is known, message undetectable	The presence of the message is known, message detectable
Message length	Long	Short	Long
Message localization	Low	Medium	High

In (Möller and Mukherjee, 2009) authors focus on using existing ontologies for defining the semantics rather than creating a custom ontology. The technique enables to annotate medical images from the anatomy and disease ontologies, storing the annotations in the headers of DICOM data (Möller and Mukherjee, 2009). Semantic Web standards OWL and RDF as a common representational basis for both medical domain knowledge and annotations was used in the work. Although DICOM data has annotations as part of the DICOM header, it can be lost after the data is compressed to become a part of a teaching or on-line collection (Table 2).

In the (Lee and Bajcsy, 2005) an information gathering system for medical image inspection is described, solving the problem of storing meta-data (image graphics, textual descriptions and original images) by using an open source Hierarchical Data Format (HDF) file format. Although HDF format is capable of storing data required, the standard storage format in medical engineering is DICOM. It is capable of storing medical data in different image formats, like native bitmap, JPEG, RLE, MPEG2, JPEG 2000, remote JPEG 2000 as JPIP stream (WEB, b), as well as waveforms, textual data and meta-data information. DICOM data is used in most data providing instrumentation, stored in most public health databases and supported by major manufactures. Thus introducing additional data storage formats is not reasonable.

Data embedding into image content is a useful technique for many applications. However, only a few applications use these methods for the semantic annotation of the medical images.

In (Nagaraju and ParthaSarathy, 2014) authors present a technique of hiding the high volume of the textual patient information in the medical images at the bit level along with security. Local Ternary Pattern (LTP) technique is used to embed the patient information into medical images for efficient storage. Local Binary Pattern (LBP) technique is mainly used for security reason of the patient information.

Authors of (Jiao and Goutte, 2010) hide medical message into DCT coefficients of the image 8×8 square blocks. Authors of (Al-Dmour et al., 2014) utilize Pixel Value Differencing (PVD) for contrast regions identification in the image and a Hamming code for embedding confidential patient information into the region of non-interest (RONI) of the cover image. In (Jiao and Goutte, 2010, Al-Dmour et al., 2014) are used information embedding methods in steganography and emphasized confidentiality and security of the medical data. Comparing with annotative their requirements differ (Table 2). The medical semantic information should be obtainable in annotated medical images for knowledge sharing.

In (Eswaraiah and Reddy, 2014) authors emphasize the usage of the fragile block based watermarking to verify the integrity of the medical image content. For this purpose, they segment the image into the region of interest (ROI), the region of non-interest (RONI) and the border region. Further, divide ROI and RONI into non-overlapping blocks and map each ROI block to a block in RONI. Information of ROI and authentication data are embedded in border pixels.

In (Coatrieux et al., 2006) the focus is on the complementary role of watermarking with respect to medical information security and management. The authors conclude that the distortionless and robust watermarking for the medical imaging may be reached using reversible watermarking methods. The reversible data hiding algorithms are not relevant to the annotative purpose as objectives of watermarking and media description are different (Table 2).

In (He et al., 2009) a high-fidelity image watermarking for annotation with robustness to moderate distortion is proposed. The high fidelity of the embedded annotations is achieved introducing a pixel domain visual model (an entropy and a differential standard deviation filters) to estimate visual sensitivity to noise. Based on that model, authors embedded two kinds of watermarks in the lapped biorthogonal transform (LBT) domain: a pilot watermark, indicating the existence of the watermark and the information watermark. High fidelity is a demanding requirement for annotating medical images using information embedding methods.

In (Manasrah and Al-Haj, 2008) robust wavelet-based image multi-watermarking algorithm is applied, capable of imperceptible embedding all needed information to manage the medical images. The multiple watermarks are devoted to image source authentication, image retrieval, medical data protection and archiving. “Annotation watermark” — the patient’s personal information, diagnosis, and health history — is embedded into the discrete wavelet transform (DWT) 2, 3, 4 level subbands — into the coefficient matrix with the maximum energy.

In the previously presented works on information embedding into image content, the annotation information is available not at the region level but only at the image level. The keywords are associated with images instead of individual regions.

In watermarking and steganography have been used 2D barcodes, too.

In (Jithin et al., 2013) work is presented watermarking scheme in wavelet domain where only some copies of 2D barcodes are inserted into the low-frequency components of the image. In (Chen, 2012) and (Chen and Wang, 2009) authors use 2D barcodes technique application for tamper detection and data concealing, respectively. They reduce QR code pattern from two dimensions to bit stream for convenient embedding into the low-frequency coefficients of the DCT.

In (Jithin et al., 2013, Chen, 2012, Kim et al., 2014, Chen and Wang, 2009) applications are used low capacity information, they are not targeted for image annotation, and there are no need to structurize information for particular regions description. Using some copies of 2D barcodes for watermarks is obviated the need to bind information from the separate blocks into one-piece text. Besides, in (Chen, 2012) and (Chen and Wang, 2009) authors convert QR codes to bit stream along with this lose some their advantages.

Watermarking and steganography are the application areas of information embedding that the primary requirements and objectives are highlighted in Table 2. Other application areas of information embedding are such as media description and image quality evaluation. These areas have some similarities (an example, imperceptibility of embedded data into a host media, limitations due to the size of the embedded data), but their requirements differ, and the same algorithm is not expedient to be used for all these areas. Concluding previous references on "watermarking annotation", we can notice all authors appeal to watermarking requirements writing about annotations. At the same time, they emphasize the security of the watermark, despite the application area. Eventually, the mentioned references are on "watermarking annotation" and the purpose of annotations — medical image management and retrieval, but not the knowledge, information mining, teaching or similar fields of application.

2.2 Evaluation of quality of the compressed annotated images

The increased volume of medical data needs more and more storage space and more time for transmission. The time to transmit an image depends on the bandwidth and the data transfer rate (bpp). A comparative analysis is given in (Ansari and Anand, 2008) among image size, bit rate, transmission bandwidth and the transmission time required, where a 12 bpp medical image of size 2048$\times$1680 requires 5.16 MB uncompressed space and will take around 23 min 54 sec for the transmission using a 28.8kB modem.

Compression of medical image data overcomes the problem of the data storage, time spent on the data transfer, bandwidth limitations, access speeds, costs, loss of the information and processing of the data. It is very important to maximize compression while maintaining clinical relevance, i. e. the compression artifacts should not be visible on the images for diagnosis.

The reversible (lossless) compression technology achieves compression ratios only between 2:1 to 4:1 (Wu et al., 2006). On the other hand, irreversible (lossy) compression schemes provide higher compression rates sacrificing the fidelity of visual information. As image compression is closely related to measurements of the image distortion, the acceptability of an image for clinical use must be determined by the distortions, appearing at the compression stage. In order to evaluate the acceptable level of compression and distortions, different studies were made (Punienė et al., 2002, Shiao et al., 2007, Sung et al., 2002).

The primary aim of the studies mentioned was to find the secure level of compression when no clinically relevant information is lost. There are some anatomical region and modalities combinations, where lossy compression must not be used. Maintaining the high image quality only in the diagnostically significant areas, the remaining regions can be encoded with low quality, using lossy compression. JPEG 2000 has a feature called ROI, and it suits the best for applications (Anastassopoulos and Skodras, 2002).

In (Punienė et al., 2002) acceptable threshold for X-Ray Angiography (XA) and US (as defined by DICOM) images, using wavelet compression is defined between 25 and 35, i. e. 0.7 – 1 bpp using JPEG 2000 alike wavelet compression. However, other authors (Shiao et al., 2007, Sung et al., 2002) have a moderate approach and compression ratios of 15:1 – 20:1 (1.2 – 1.6 bpp) are nearly the limit of CT, MR, CR and NM image acceptability for clinical use. The compression ratio of up to 50:1 (0.48 bpp) can be used in very specific cases. Again, the results are for JPEG 2000 compression, as distortions in JPEG image are unacceptable for this compression ratio.

We refer to the Canadian guidance for radiologists (WEB, a). The summarizing table of lossy medical image compression is provided in Table 3. Abbreviations of modalities for Table 3: CR/DR (Computed Radiography / Digital Radiography), CT (Computed Tomography), US (Ultrasound), MR (Magnetic Resonance), NM (Nuclear Medicine).

Table 3. Maximal compression ratios for anatomical areas and DICOM modalities, based on (WEB, a)

Anatomical area	Compression method	**Modality**				
		CR/DR	CT	US	MR	NM
Vascular	JPEG JPEG 2000		15:1		24:1	
Body	JPEG JPEG 2000	30:1	15:1 10:1	12:1	24:1	
Breast	JPEG JPEG 2000	25:1		12:1	24:1	
Chest	JPEG JPEG 2000	30:1	15:1			
Musculoskeletal	JPEG JPEG 2000	30:1 20:1	15:1	12:1	24:1	
Neuroradiology	JPEG JPEG 2000		12:1 8:1		24:1	
Pediatrics	JPEG JPEG 2000	30:1	15:1	12:1	24:1	
All NM	JPEG JPEG 2000					11:1

Information content weighted structural similarity measure (IW-SSIM), based on the Structural Similarity Index (SSIM) and its multi-scale variant (MS-SSIM) as the state of the art metrics were chosen to measure the quality and fitness of the image to particular compression type and to the particular number/length of annotations (Wang and Li, 2011, Wang et al., 2004, Wang et al., 2003).

An existing objective measurements of medical image quality, such as mean squared error (MSE) and peak signal to noise ratio (PSNR), are directly related to the diagnostic accuracy of the medical images. They are not directly related to human perception and does not provide satisfactory results (Wang et al., 2004) because there are different characteristics of medical image contents, image formats, and users. For the medical image quality evaluation, we need to automate objective quality assessment methods that are guided by the human vision model in order to reflect human perception accurately.

The users of medical imaging systems, typically physicians, focus on particular ROI in a medical image. The quality of other regions may be irrelevant for diagnostic accuracy. The characteristics of medical images differ from that of natural images, exposing huge volumes of tightly packed data in high dynamic ranges — from 8 up to 16 bits per single information channel.

3 Proposed algorithm for semantic annotation of medical images

The requirements have been raised to the quality of medical images, especially for regions that indicate the pathology. The problems that have been met in the embedding process of annotations into the content of medical images are evaluated, and the requirements for embedding are defined in the successive section. In the subsection 3.2 is presented the annotative algorithm under consideration of JPEG 2000 standard.

3.1 Usage requirements

The requirements and technical problems for the region-based medical image descriptions have been proposed and presented in Table 4.

In consideration of the problems mentioned above, the annotation of the medical image should not be stored in the same spatial region as the interested image region (ROI). It can be detached and stored elsewhere in the same image. There are two aims of annotation detaching:

1. Increasing the capacity of annotation, when it does not physically fit within ROI.
2. Preservation of quality in ROI.

Medical images are stored in a particular format called DICOM, encapsulating both image ant metadata. DICOM defines two ways of storing of obtained image data (WEB, b): Native format and Encapsulated format. Native format is unencoded bitstream as the direct concatenation of Pixel Cell bits, starting from LSB. Encapsulated formats include JPEG, RLE, JPEG-LS, JPEG 2000 and MPEG2 MP@ML / MP@HL

Table 4. Basic requirements and technical problems for medical image annotation

Requirements	Technical problems
1. Regions to be described may have any shape. 2. Annotations may contain any binary data. 3. The need to transmit annotations separately must be avoided. 4. The annotation should allow to present multiple regions with a single descriptive data. 5. It would be reasonable to keep the quality of the pathological regions. 6. It would be reasonable to keep the samples in the initial Hounsfield scale range. 7. The extraction of annotations should not depend on current image quality. 8. All embedded data belonging to regions shown on the screen must be retrievable without any additional transmission of any data.	1. The number and the length of embedded annotations are limited by the provided capacity and quality of the host image. 2. Strict professional standards and desired level of compression create the tight space for any additional information. 3. The typical image size of most modalities is 512-by-512 pixels. As the image is in most cases centered, the size of the area, containing useful information is in the range of 400-by-450 pixels. The annotative area may be as small as 5-by-5 pixels. 4. Annotations usually have high amount of data.

image formats. As defined in (WEB, b), "the context where the usage of lossy compression of medical images is clinically acceptable is beyond the scope of the DICOM Standard."

The particular interest is in JPEG 2000 image format, as other ones are widely used in different fields of application. The compression for JPEG 2000 is still computationally intensive procedure, and it takes times longer to compress the image than to decompress it. Due to the proper crafted encoding blocks, called "precincts", no one ever should need to re-compress the image as the same compressed image can be transmitted and displayed at different levels of resolution, chromaticity or size. This sounds promising for JPEG 2000, as the image can be evaluated as distributed resource, identified by uniform resource identifier (URI) instead of the physical file. This in turn means there is no more the "single copy" that must be preserved.

3.2 Embedding of region-based annotations

Medical image, like the other types of digital images, can be represented by a series of stationery components, each representing the particular aspect of the image. For example, signals of low-frequency presents general shape of the image, medium frequencies add image details, and high-frequency signals contribute finest details and noise in the image. The approach is the generalization of widely used frequency or wavelet image analysis methods. Denoting I_c as particular image component, f as a function transforming component I_c to $\mathbb{N}^2$ space and n as a coefficient, determining the significance of the component, image I ($I \in \mathbb{R}$) can be composed as:

$$I = \sum_{c=1}^{m} nf(I_c). \tag{1}$$

The count of image components m is application - specific, as well as the boundaries between image components. To embed the information into the digital image, we substitute chosen image component I_c with the block of information P_c we need to embed. Denoting α as embedding strength and k as embedding key, the (1) eq. becomes:

$$I = \sum_{c=1}^{m} nf(I_c \bigcup \alpha k(P_c)). \tag{2}$$

The embedded block P_c may entirely or partially replace the image information component I_c. The I_c and P_c may not be of the same domain — like embedding frequency-based P_c into I_c in spatial domain, while image generation is based on the domain of I_c.

The selection of I_c depends on the requirements for information embedding. Selecting I_c in the high importance region, the information becomes more visible. Selecting I_c in low importance regions, the embedded information is less noticeable, but may be lost during re-compression, change of image format and routine image processing — sharpening, blurring, rotation, etc.

In the algorithm, the I_c are quantized indexes of DWT decomposition, P_c are bit masks and f is the complex function of dequantization and inverse DWT transformation.

The key point for information embedding is the selection of suitable regions in the image. An image is subdivided into several types of principal regions R, as shown in Figure 1:

1. Image features, containing important information. These areas will be referred as Region of Interest (ROI) further on. It is reasonable to keep the maximal quality Q_{max} for this region.
2. Regions, containing secondary information. They will be referred as Region of non-interest (RONI). RONI also includes the background, filling the image to the rectangular shape or capturing details of the environment. Minimal image quality Q_{min} is allowed for these areas.

Quality metrics $R_i(Q)$ are then assigned to every region. We initially presumed no information should be embedded into the principal regions (ROI) of an image, in order to keep the image suitable for diagnostic purposes. Thus, we had two sets of regions: the region where the annotation was to be embedded (Region of Annotation, ROA) and the ROI. The placing of ROA is either manual or automatic, and it accommodates the entire length of the annotation.

The 2D Quick response (QR) codes were chosen as the physical carrier of the information. It allowed us to exclude the creation and verification of the encoding and error correction stages of the experiment.

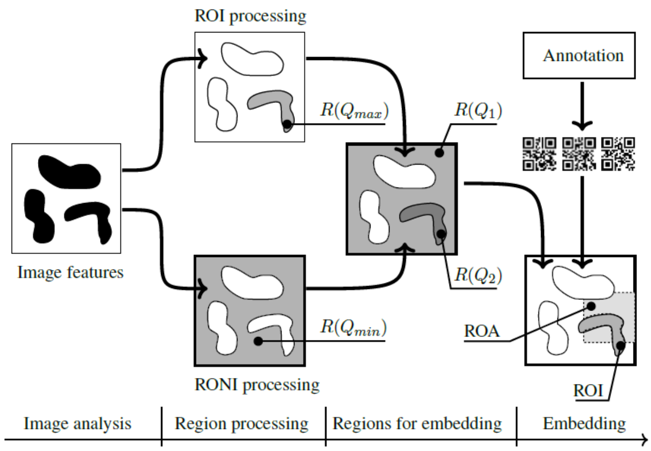


Fig. 1. Principal steps for the embedding area classification

The design of QR codes allows quick decoding of the information when part of the carrier may be lost, but they tend to increase in size when a large amount of data is encoded. The larger the QR code, the less is the fill-factor — the ratio between the area available and the area used — of the ROA. To overcome the growth of the QR code, we split the entire annotation into the chunks and added the supporting information. It allowed to keep the size of QR reasonable and the fill-factor of the ROA in the highest level possible. Moreover, the split encoding allows arbitrary placement of the QR codes, so the ROA can take any shape and avoid the regions of the higher image quality.

Based on these presumptions and the requirements described in Table 4, the following image annotation scheme (Figure 2) was developed and placed into the test environment:

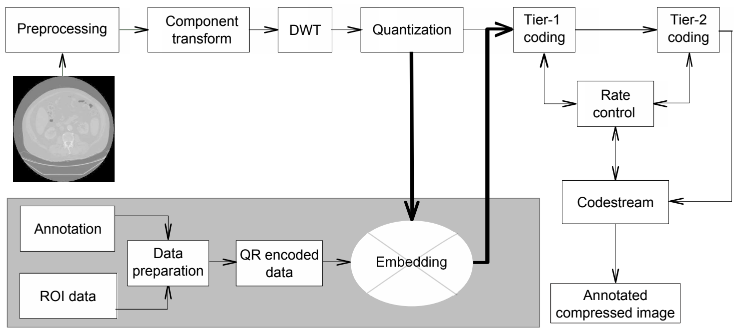


Fig. 2. Developing diagram for information embedding in JPEG 2000

1. Collecting data for embedding. This step includes the annotation itself and the region of interest.
2. Preparation of the information to be embedded. This step transforms annotation to the form, suitable for embedding, applying lifting schemes if necessary.
3. Selecting (or pointing) the region to embed the annotation.
4. Partial decoding (or partial encoding) of JPEG 2000 image data.
5. Embedding the information to the quantization coefficients of JPEG 2000 image data.
6. Encoding JPEG 2000 image data. This step is expected to be recursive if the information must be accessed in some particular manner (e. g., at the predefined level of detail or chromaticity).

The standard JPEG 2000 image compression workflow is used for the information embedding in steps 5 and 6, and no additional DWT decomposition and quantization steps should be performed. This approach allows to reduce calculation cost in the embedding and decoding stages. The proposed algorithm is developed to deal with the problems and requirements mentioned below:

– Due to the high amount of annotating data, spatial collocation of ROA and ROI is impossible in small areas. The annotation is embedded outside the ROI, thus leaving more space for annotations and preserving the information fidelity in the area of ROI.
– Additional fields are added to the annotation in order to support shifting ROA out ROI. Additional metadata fields are added to the annotation structure to support shifting ROA out ROI and encoding the arbitrary shape of the annotation.
– As ROI and ROA are no longer spatially related, the ROA can be embedded in diagnostically irrelevant regions, allowing more information to be embedded and image distortions to happen.
– Detaching ROA from the ROI allows to annotate the arbitrary size and shape of the ROI.

The annotation consists of informational fields, identifying the spatial location of ROI, its shape, and contents. The linear structure of the annotation is arranged in a way allowing fast identifications of ROI and its shape. After the arrangement, linear structure of the annotation is divided into embeddable chunks and transformed into the 2D barcode (Figure 3), widely used for labeling purposes in various fields of industry and medicine. Use of standard 2D barcode allows to rely on the existing proven solutions in the fields of error-correction, reliable information encoding, and automatic spatial identification.

The annotation is embedded into the entire tree of DWT decomposition, allowing partial image transmission and reconstruction of annotation. LL (lowpass, lowpass) subband, being the most sensitive for alternations, to minimize the influence of alterations in the image quality is not used for annotation embedding in particular cases — when the medical image has no diagnostically irrelevant regions.

The algorithm allows the image to be annotated many times until the limit of the informational capacity is not reached.

Fig. 3. A region of bit plane of DWT decomposition with annotation embedded

It is possible to edit and remove the annotation, although the removal of the annotation will not restore the quality of the image. Relocation of the ROI is possible as far as its shape and size remain constant.

The ROI can be selected manually, describing image sub-area with rectangular, circular or other shapes which precisely selects a set of pixels of interest. Semi-automated or automated methods can be used to select ROI, like image threshold, segmentation, and clustering (especially for regions of the irregular shape).

To retrieve the embedded information, the image must be processed up to dequantization stage. Due to the selected embedding strategy, the embedded information is progressively available as it is decoded from the local file or received from the remote server. As the physical carrier of the embedded information is the QR code, the quality of retrieved information and possible information loss is highly dependent on the carrier and allows to restore up to 30% of the information using embedded error-correction codes (WEB, c).

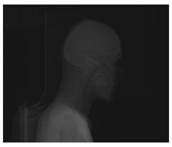
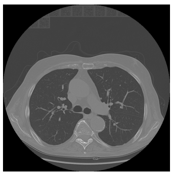
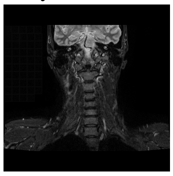
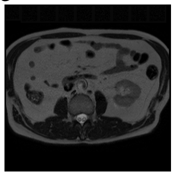
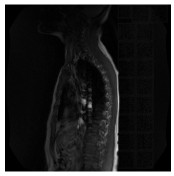
4 Experimental results and discussion

To get an initial evaluation, a set of DICOM images provided by the team of medical physics of the Institute of Oncology of Vilnius University was prepared and submitted to the clinical radiologists for the assessment. The set contained the images mostly from MR and CT modalities — the most commonly used ones. The information was embedded both in clinically relevant and irrelevant areas, starting with the lowest (LSB) up to a 12th bit plane. The experts scored the visual distractedness of the embedded information for the ordinary diagnostic tasks. We need to notice significant disagreements among specialists in the image quality when evaluating annotations embedded in the middle and high bit planes. So the score is treated as average, and more detailed evaluations should be gathered for every anatomical region, clinical case and modality. The Mean Opinion Score (MOS) metrics was calculated and is presented in Table 5. The heading of every column presents the annotated image with MOS score not lower than 4 and the information embedded into the highest decreasingly MOS scored bit plane.

As the embedding was performed in the Pixel Data domain of DICOM image (either plain or compressed one), additional care must be taken about:

a) $RescaleSlope$ and $RescaleIntercept$ DICOM values to ensure correct acquired value (like Hounsfield units or Optical Density) reconstruction for future analysis, and

Table 5. Expert evaluation of distractedness of the embedded information, MOS metrics (scale 1 to 5, higher the better)

Bitplane for annotation	Clinically irrelevant region				
					
1	5.0	5.0	5.0	5.0	5.0
2	5.0	5.0	5.0	5.0	5.0
3	5.0	5.0	4.7	5.0	5.0
4	5.0	5.0	3.3	5.0	5.0
5	4.7	5.0	1.7	3.7	5.0
6	4.0	5.0	2.0	2.0	4.7
7	2.7	4.7	3.0	1.0	3.0
8	3.0	4.0	2.7	2.7	2.7
9	2.7	3.3	3.0	3.7	2.7
10	2.3	3.7	3.3	4.3	3.3
11	4.3	4.0	3.3	4.7	4.3
12	4.7	3.7	3.7	5.0	4.7

b) remain at the same acquired value's range to ensure correct data windowing in the future.

These restrictions can be neglected when embedding data outside clinically relevant areas, although the embedded data may appear as visual distractions when specific windowing ranges are used.

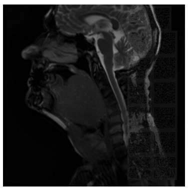
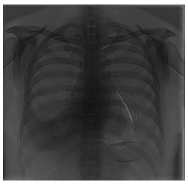
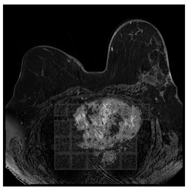
We have considered the subjective evaluation of clinical radiologists when preparing created algorithm for the testing. In JPEG 2000 based algorithm was used 3 level wavelet decomposition. Information was embedded into the six lowest bit planes of the compressed domain because the visual distractedness of the embedded information was least perceptible in these cases as presented in Table 5.

Images chosen for the testing of created algorithm were free DICOM image sets, downloaded from (WEB, d). As the annotation was physically separated from ROI, the diagnostic quality of the annotated image did not depend on the size or shape of ROI, but on the number and length of the embedded information.

Three sets of annotations were used for every image: a single annotation of 5 words; a single annotation of 20 words; a set of 3 annotations, 5, 20 and 100 words each. The text chosen for every annotation is "Lorem ipsum…", varying the length of the text to 5, 20 and 100 words. The average values of medical images quality were evaluated for the presentation of the experimental results.

The annotations were embedded in the clinically irrelevant areas. Whereas annotation does not alter the clinically relevant areas, the visual fidelity of the image is not the most important issue.

Table 5, continued

Bitplane for annotation	Clinically relevant region		
			
1	5.0	5.0	5.0
2	5.0	5.0	5.0
3	5.0	5.0	5.0
4	5.0	5.0	5.0
5	5.0	5.0	4.7
6	5.0	5.0	4.3
7	4.0	4.7	4.0
8	2.7	1.0	2.7
9	2.7	2.7	3.3
10	3.7	3.0	3.7
11	3.3	2.3	3.7
12	3.7	4.0	2.0

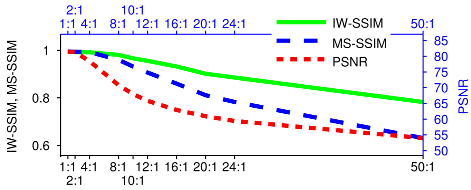
Two the most common image cases from the entire test set are chosen for presentation in the article: like MR images, presented in Figure 4, the results given in Figure 5, and like OT images (XA according to the latest DICOM specification), presented in Figure 6a, the results given in Figure 7.

The grid-like patterns on the central part of Figures 6b and 6c are the embedded annotations. The patterns of the regions suggest the distortions appear due to the intensive use of DWT decomposition tree when the annotation is embedded to every subband of every decomposition level. The data embedded in LL subband (Figure 6c) appears more blurry compared to one with excluded LL subband (Figure 6b) but no significant difference in visual quality is noticeable. The data appears more blurry when embedded in higher DWT decomposition levels compared to one in the lower DWT decomposition levels too.

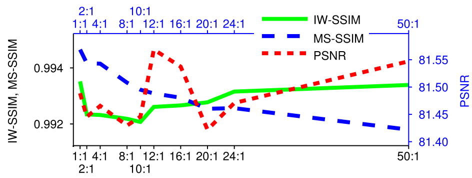
Figures 5a and 7a compare the visual quality of the original and annotated images. Although the quality of the annotated and compressed image decreases rapidly, it is comparable to the loss of image quality due to compression, as presented in Figures 5b and 7b.

The fundamental problem is the informational capacity of the medical image (like MR or CT modalities). To increase the capacity, the LL subband of DWT decomposition can be used for embedding, and this poses the potential problem of reducing visual fidelity. To clarify the influence of LL subband, the information was embedded to the LL subband and visual quality metrics were calculated (Figures 7c, 7d). The numbers, presented in Table 5 reveal the minor impact on the image fidelity and exposes the problem of the image size. Creating more than three levels of DWT transformation leaves no space for embedding in the image, sizing from 256×256 or 512×512 pixels, as the

Fig. 4. Image "MR-MONO2-16-head" with annotation embedded, compression ratio 2:1. The ROI is highlighted, and the recovered annotation of 50 words presented aside



(a) MR modality with data embedded, compared to original DICOM image (average values)



(b) MR modality with data embedded, compared to compressed DICOM image at the same compression ratio (average values)

Fig. 5. Evaluation of image quality: annotated MR modality image

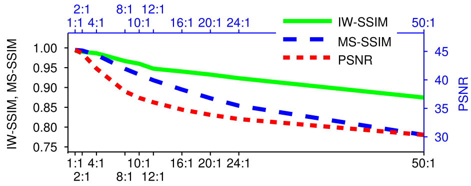
(a) Original image

(b) Information embedded into LH, HL and HH subbands

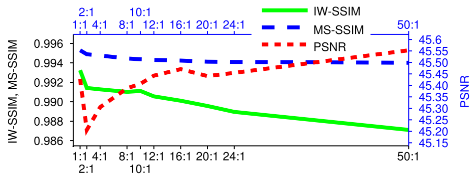
(c) Information embedded into LL, LH, HL and HH subbands

Fig. 6. Original image "OT-MONO2-8-a7" (XA modality) and at compression ratio 50:1, with annotation embedded into clinically irrelevant area

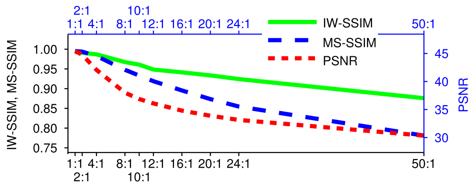
size of a single subband becomes smaller than 32×32 pixels. The minimal QR version 2 code block to be embedded is 25×25 pixels. The use of the smaller, QR version 1,



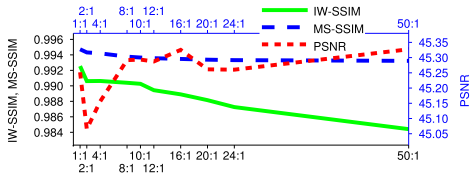
(a) annotated image (HL, LH and HH subbands) compared to the original DICOM image (average values)



(b) annotated image (HL, LH and HH subbands) compared to the compressed DICOM image of the same compression ratio (average values)



(c) annotated image (all subbands) compared to original DICOM image (average values)



(d) annotated image (all subbands) compared to the compressed DICOM image of the same compression ratio (average values)

Fig. 7. Evaluation of quality in the annotated XA (OT) modality

code blocks is not suggested, as the ration of informational capacity over the area used is quite small.

Figures 7c and 7d show the influence of alteration in the LL subband to the image fidelity: it tends to reduce image quality in all modalities, slightly reducing PSNR values while keeping IW-SSIM and MS-SSIM at almost the same level.

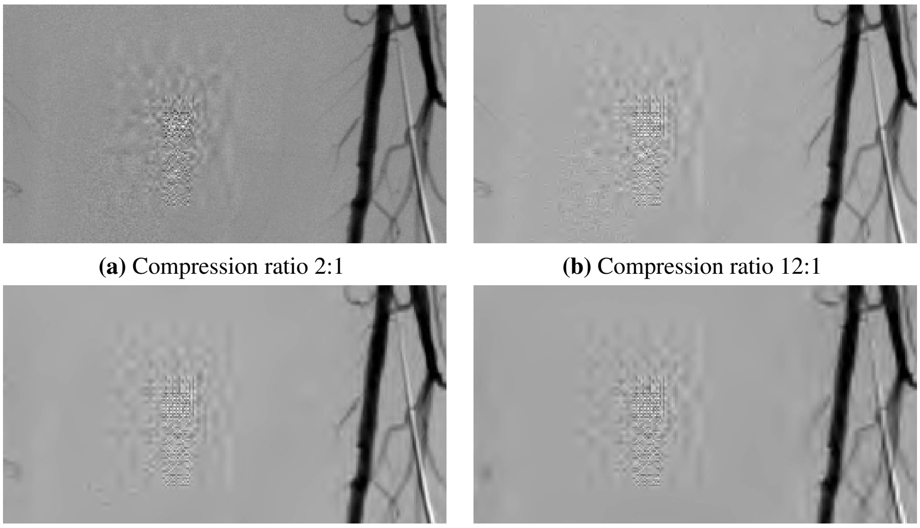
In Figure 8 are displayed XA images, undergone compression using various compression ratios. It is quite obvious the loss of small to medium details in high compression ratios (Figure 8c compared to Figure 8a) and the "ringing" pattern (Figure 8d compared to Figure 8a), while medium compression ratios, presented in Figure 8b display acceptable image quality and compression performance.

5 Conclusions and future work

In this paper, the medical image annotating algorithm for embedding semantic descriptions about corresponding ROI's directly into RONI of image content is proposed. The QR codes with structurized information chunks are embedded into partially compressed image content considering the evaluation of clinical radiologists.

It is possible to embed information into the regions of JPEG 2000 encoded medical image and retrieve it using 2D barcode as the information carrier.

Slightly bigger distortions in the image data caused by embedding information to LL subband. However, LL subband is rarely used for information embedding because



(a) Compression ratio 2:1 **(b)** Compression ratio 12:1

(c) Compression ratio 24:1 **(d)** Compression ratio 50:1

Fig. 8. Part of the annotated image “OT-MONO2-8-a7” with applied different compression ratios

it gives no additional space for annotation as in clinically irrelevant as in relevant regions. More compact forms of 2D barcode are to be used in the higher levels of DWT decomposition.

Despite either LL subband was used for embedding or not, embedded annotation may appear in the image.

The quality of annotated and compressed image degrades slightly more, but it is comparable to the image quality loss due to image compression. Due to placing annotation to diagnostically irrelevant areas, the image is still usable for diagnostic purposes.

Future experiments will also be directed to the development of the annotation algorithm based on JPEG standard. JPEG format is motivated as it is encapsulated DICOM format and widespread among various users.

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Received October 4, 2015 , accepted November 12, 2015