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Application of Novel Lossless Compression of Medical Images Using Prediction and Contextual Error Modeling

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A B S T R A C T

Conduction of tele-3D-computer assisted operations as well as other telemedicine procedures often requires highest possible quality of transmitted medical images and video. Unfortunately, those data types are always associated with high telecommunication and storage costs that sometimes prevent more frequent usage of such procedures. We present a novel algorithm for lossless compression of medical images that is extremely helpful in reducing the telecommunication and storage costs. The algorithm models the image properties around the current, unknown pixel and adjusts itself to the local image region. The main contribution of this work is the enhancement of the well known approach of predictor blends through highly adaptive determination of blending context on a pixel-by-pixel basis using classification technique. We show that this approach is well suited for medical image data compression. Results obtained with the proposed compression method on medical images are very encouraging, beating several well known lossless compression methods. The predictor proposed can also be used in other image processing applications such as segmentation and extraction of image regions.

***Key words**: telemedicine, medical images, lossless compression*

Introduction

Many applications such as medical imaging, high precision and 3D image analysis[1,2], visualization, tissue modeling, transmission of medical images, image storage and archival, which provide scientific expertise necessary for developing successful 3D-computer assisted surgery (3D-CAS), Tele-3D-CAS, and virtual reality (VR) applications, deal with a vast amount of image data. The mentioned technologies represent a basis for realistic simulations that are useful in many areas of human medicine, and can create an impression of immersion of a physician into a non-existing, virtual environment. Such an impression of immersion can be realized in any medical institution using advanced computers and computer networks that are required for interaction between a person and a remote environment, with the goal of realizing tele-presence[3]. All those applications and many others demand that no loss occurs in the process of compression, which implies that lossless image compression techniques must be employed.

An important aspect in the design of the lossless compression algorithm is separation of the model and the coder[4]. The role of the coder is to encode the information supplied by the model. The goal of the model is to detect and remove redundancy in the information source and to supply the coder with decorrelated data. The more redundancies are detected and removed by the model, the better compression is achieved. Optimal coding is well known in the form of arithmetic coding[5]. This means that the main problem is the design of effective model for the data under consideration.

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Collaborative work

Before the introduction of DICOM standards, image recordings were stored on films, where the information obtained from the diagnostic device was in part lost. In ideal conditions, sixteen different image levels could be distinguished on films at the most. When film images were to be stored in computer systems, films had to be scanned, thus inevitably losing a part of significant data and probably introducing some unwanted artifacts. The level setting and window width to be observed on the images could not be subsequently changed. Visualization of the image on the diagnostic device monitor was of a considerably higher quality, thus it was quite naturally used for record receipt and storage in computer media. Video image allows for the receipt of 256 different levels at the most. Neither it is possible to subsequently modify the level setting and window width to be observed on the images that have already been stored in the computer system.

When stored in computer systems by use of DICOM protocol, images are stored in the form generated by the diagnostic device detector. These image recordings can then be properly explored by use of powerful computer systems. This is of special relevance when data in the form of images are to be used for complex examinations and testing, or in preoperative preparation where rapid and precise demarcation between the disease involved and intact tissue is required. It is also very important for the images to be visualized in various forms and from different aspects and then – which is most demanding indeed – to develop spatial models to aid the surgeon in preparing and performing the procedure as well as in postoperative analysis of the course of the procedure.

The entire operative procedure can be simulated and critical areas avoided during the real procedure by employing real patient images in the operation preparatory phase using complex spatial models and simulated operative field entry (Virtual Endoscopy, Virtual Surgery)[2]. 3D-CAS, VR, and Tele-3D-CAS systems can be used for education, assessment of work skills, training, simulation, 3-D visualization, computer-aided design, teleoperation, and telemanipulation. If we look at various application areas, we see that one of the more popular VR application areas is medicine. A specific area of surgery is minimally invasive surgery (MIS). Learning an MIS technique is more difficult than learning open surgery techniques because there is no tactile information, an indirect field of view is available, and there are difficulties in hand-eye coordination. 3D-CAS systems may be used to aid delivery of surgical procedures. In fact, the most useful systems are augmented reality systems, which combine patient image with images obtained using various medical imaging modalities such as CT, MR, and ultrasound.

During the course of our Three-Dimensional Computer Assisted Functional Endoscopic Sinus Surgery (3D-C-FESS) method development, a variety of program systems were employed to design an operative field model by use of spatial volume rendering techniques. Initially, the modeling was done by use of the VolVis, Volpack/Vprender and GL Ware programs.

Computer assisted telesurgery

One of the simplest telemedicine applications is medical teleconsultation, where physicians exchange medical information, over computer networks, with other physicians in the form of image, video, audio, and text. Teleconsultations can be used in radiology, pathology, surgery, and other medicine areas. One of the most interesting telemedicine applications is telesurgery. Telesurgery (such as www.mef.hr/modernrhinology) is a tele-presence application in medicine where the surgeon and the patient are at different locations, but such systems are still in an early research phase. Patients, who are too ill or injured to be transported to the hospital, may be operated remotely. In all these cases, there is a need for a surgeon specialist who is located at some distance.

Modern equipment such as the endo-micro cameras show the operative field on the monitor mounted in the operating theater; however, the image can also be transmitted to a remote location by use of video transmission. The latest computer technology enables receipt of CT images from a remote location, examination of these images, development of 3D spatial models, and transfer of thus created models back to the remote location. All these can be done nearly within real time. These procedures also imply preoperative consultation. During the surgery, those in the operating theater and remote consultants follow on the patient computer model the procedure images, the »live» video image generated by the endoscopic camera[6], and instrument movements made by the remote surgeon. The main idea considering the use of computer networks in medicine is: it is preferable to move the data rather than the patient.

Materials and Methods

Predictive image coding in which the prediction error of the current pixel is coded has been shown to be the most effective technique in lossless image compression. Using prediction, the image data are decorrelated prior to the entropy coding so that better compression is achieved. In the framework of sequential, backward adaptive lossless image compression, predictive image coding can be formulated as composed of the following steps:

1. Prediction of the current pixel based on the casual set of surrounding pixels – pixel prediction.
2. Determination of the conditional probabilistic context in which the current prediction error occurs – error modeling[7].
3. Coding of the prediction error in the detected probabilistic context – entropy coding.

Figure 1 shows the main blocks of the predictive image compression method proposed. All building blocks will be explained in the following subsections.

An important property of image data is the high degree of correlation among neighboring pixels so that it is

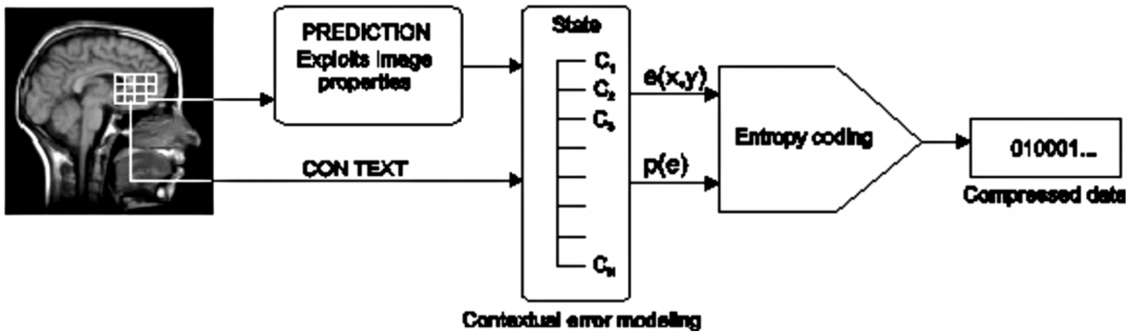

Fig. 1. Block scheme of proposed compression algorithm.

possible to decorrelate samples using some sort of pixel prediction. If the predictor can effectively model this spatial correlation among neighboring pixels, then the remaining prediction error will be mostly decorrelated and easily coded with an entropy coder. On the other hand, it is well known that image data are nonstationary, which means that the properties of image regions vary all over the image[8]. Accordingly, if the predictor is supposed to predict well in various image regions, it is necessary to switch its own properties so that it can adjust to the changing image characteristics. Another assumption of local stationariness is very well applied to the image data. This means that for arbitrarily small image regions, the predictor adjusted to the dominant local property will predict well inside the region, but it has to be highly adaptive to varying image regions.

Image is treated as two-dimensional array $I(x,y)$ of pixel grey intensity values with the width W and the height H, where $0 \le x < W$ and $0 \le y < H$. Pixels are observed sample by sample in raster scan order, from top to bottom, left to right. In the assumed backward adaptive approach, the encoder is allowed to use only past information that is also available to decoder. This means that to form the prediction only previously observed pixels are used, as shown in Figure 2. In fact, only a small subset of previously encoded pixels is used to form the causal template $\Omega(x, y)$. Figure 2 is an enlarged segment from Figure 1 and depicts the main elements of the predictor which uses causal context of surrounding pixels $\Omega(x, y)$ for the prediction of current pixel $I(x, y)$:

$$\hat{I}(x,y)=f(W(x,y)). \tag{1}$$

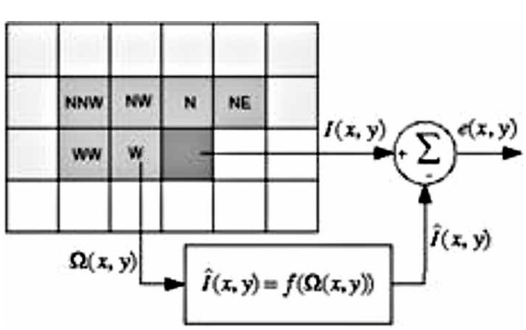

Fig. 2. Pixel prediction.

For convenience, the compass point notation for surrounding pixels is used, for example N denotes North pixel, W denotes West pixel from the current pixel, etc. Instead of coding the real pixel value $I(x, y)$, the pixel prediction $\hat{I}(x, y)$ is performed and the prediction error $e(x, y) = I(x, y) - \hat{I}(x, y)$ is produced.

Typical image can be treated as being composed of regions with varying dominant properties. Those properties pose different and conflicting constraints on the prediction function. If we consider linear prediction function:

$$\hat{I}(x,y)=f(W(x,y))= \sum_{I(i,j)\hat{I}W} a_{i,j} \times I(i,j), \tag{2}$$

Then we can put the following constraints on the predictor coefficients $a_{i,j}$ depending on the dominant property of the current region[9]. Smooth regions in which the intensity of pixel does not change require that $\sum a_{i,j} = 1$. On the other hand, for planar region it is required for at least one of $a_{i,j}$ to be negative so that the gradient can be estimated. Noisy regions require that the least magnitude of noise is introduced into the prediction, which implies that $\sum |a_{i,j}| = 1$ should be as small as possible. Edges and textured regions comprise the most important visual part of images[9]. Edges require some kind of mechanism in the predictor to provide the detection and orientation of the edge. Textures are most difficult to model and for the sake of prediction they can be considered as a combination of noise and edges.

We modeled image regions as a combination of the above structures with the presence of the dominant property. Therefore, the choice for the predictor to satisfy given constraints is rather complex and demanding and an adaptation mechanism is required. The best choice for the dominant property in case of a blind model is to assume that the noise dominates and to take corresponding constraint as suggested by Seeman et al.[10]. However, the effectiveness of any prediction scheme depends on its ability of adapting to different image region properties. This precludes the use of static predictors if efficient prediction is required. Typical heuristically tuned switching predictors use a set of static prediction functions and heuristics to determine which function will be used for the prediction of the current pixel. Such predictors include GAP (CALIC algorithm[11]), MED (LO-

CO-I, JPEG-LS standard[12]), etc. The main drawback of this approach is the lack of robustness in the presence of nontrivial image regions. Another approach is to use adaptive predictor as in the prediction scheme proposed. There is a big spectrum of adaptive predictors with various mechanisms of adaptation and complexities such as LS-based predictors[13], blending predictors[9]. The aim of the prediction scheme proposed in this paper is to predict well in all various image regions with moderate computational complexity.

Classification and blending predictor CBP

The predictor proposed is based on the idea of blending predictors from Seeman and Tischer[8], which is further extended with dynamic classification of predictor context on a pixel by pixel basis. The set of predictors $F=\{f_1,f_2,...,f_N\}$ is composed of N static predictors adjusted to predict well in the presence of specific property. For example, simple predictor W predicts well in the presence of sharp horizontal edge. We set F to be $F=\{N,W,NW,NE,N+W-NW,G_w,G_N\}$ where $G_W=2N-NN$ and $G_N=2W-WW$.

The classification process determines the set of neighboring pixels on which the blending of F is performed. It is similar to the initial step of VQ design substantially simplified in order to be usable in symmetric, backward adaptive algorithm[14].

Our predictors can be described as follows: every pixel in the image has its own template VT, which is composed of four already observed neighboring pixels, as shown in Figure 3, enlarged segment. On the large window of previously observed pixels such as shown in Figure 3 we will find M pixels with the most similar template to the template of the currently unknown pixel (in our experiments we set M to be seven). We call the process classification and the result the set of similar pixels. The similarity is defined as Euclidean distance between templates. Figure 3 shows the possible outcome of the classification: seven similar pixels and their templates.

The next step is to train our set of predictors F on the chosen set of similar pixels. If the predictor $f_k \in F$ predicts poorly on the set of classified similar pixels, then it will get large penalty G_k, but if it predicts well, then he will get small penalty. After the complete process for every predictor and every pixel from the chosen set is done, we have a set of predictors $F=\{f_1,f_2,...,f_N\}$ and set of penalties $\{G_1,G_2,...,G_N\}$ and the final prediction will be:

$$\hat{I}(x,y)=f_P(x,y)=\left[\frac{\left(\sum_{k=1}^{N}\frac{1}{G_k}\times\hat{I}_k(x,y)\right)}{\sum_{k=1}^{N}\left(\frac{1}{G_k}\right)}\right] \quad (3)$$

The prediction for the current pixel is the weighted sum of predictions of all the predictors from F with weights inversely proportional to the corresponding penalties. The penalty of predictor reflects its efficacy on the blending context. If the predictor predicts well, its contribution in the final prediction will be higher, thus it has more chance to produce precise current prediction. The predictors that do not predict well on the current blending context will eventually be blended out by associated large penalties. The denominator in (3) normalizes the final prediction.

Finally, we track the efficiency of our final predictor from (3) and record its typical error as an average sum of errors on the classified set of pixels. This typical error is used for refinement of our prediction. We call this step error correction.

Our predictors allow other nondominant properties to be included (modeled) in the prediction, although with less contribution. This is crucial difference compared with switching predictors that do not have the capability to model nontrivial image structures with a mixture of properties. Note that pixels from the search window that do not belong to the region with the same dominant property as the region in which the current pixel resides will not be included in the current cell and thus they will not be part of the blending context. In case that one of the penalties is zero, the corresponding predictor is used for prediction without any other additional steps. In this way, the perfect predictor gets the chance to predict the current pixel. On the other hand, if all the penalties dif-

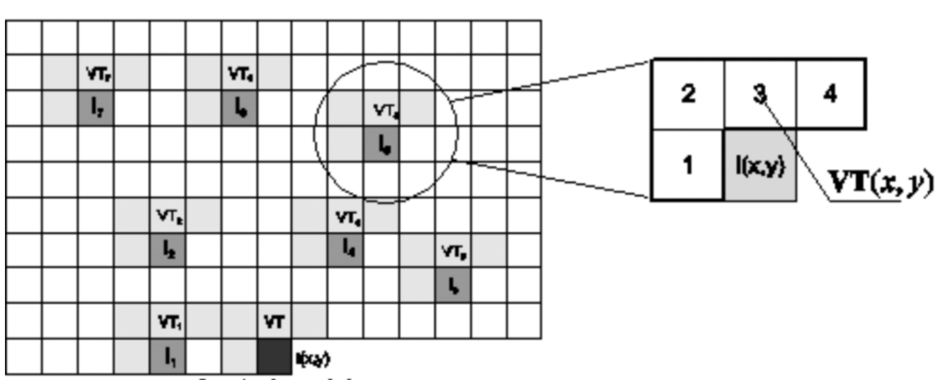

Fig. 3. The set of similar pixels to the current pixel.

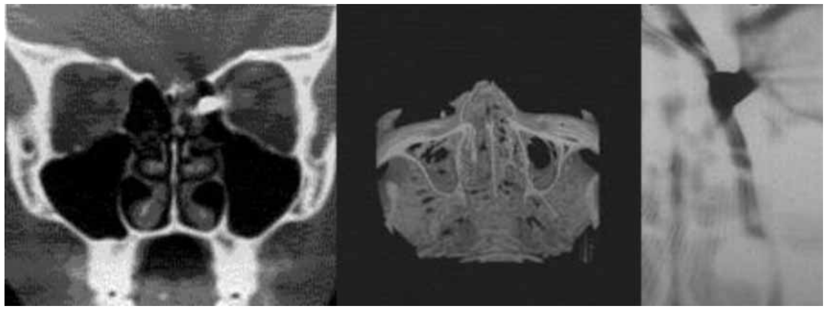

Fig. 4. Foreign body in the region of the left eye.

fer from zero, we get the averaging prediction through the blending process. This is the good choice, since the most important property that is to be assumed for images is the presence of noise[9].

Contextual error modeling

Although the prediction step removes statistical redundancies within image data, in the error image there are remaining structures that cannot be completely removed using only the previously applied prediction step[7]. Those structures are removed using contextual modeling of prediction error, where the context or the state is the function of previously observed pixels, errors or any other relevant variables. As reported by Wu, the heuristic method that uses both previous pixel template and causal error energy estimate is best suited for this purpose[5]. Wu's contextual model is composed of two different submodels: (1) a model with a large number of states that is used for prediction error feedback, and (2) a model with a low number of states used for error probability estimation. On the other hand, Wu's predictor is a heuristic predictor with a low degree of adaptation, and our proposal is a highly adaptive predictor with already built in error feedback mechanism (error correction step in the prediction phase). This implies that our mechanism needs only a small contextual model for estimation of symbol probabilities. Our contextual model is built as follows: besides the high correlation with texture pattern, current prediction error is also highly correlated with the errors on neighboring pixels. This is modeled using the error discriminant on previous pixels: $\Delta = d_h + d_v + 2|e_w|$, where $d_h = |W - WW| + |N - NW| + |N - NE|$ and $d_v = |W - NW| + |N - NN| + |NE - NNE|$ are horizontal and vertical gradients around the current pixel, and e_w is the prediction error on the west pixel W. Δ is uniformly quantized into eight levels to produce the state of the model. Every state contains a histogram table which is used for probability estimation of the prediction error in the current state. Because of the context dilution effect, this context is required to have a small number of states.

Entropy coding of prediction error

The final step of the image compression algorithm proposed is entropy coding of the resulting prediction error. For the given error symbol and given probability estimate computed from the contextual state, the codeword is computed by the entropy coder. This codeword is output as the final result of pixel compression process. Our proposal uses highly efficient implementation of arithmetic coding[5].

Past experience and system implementation

In the late 1990s, a scientific research rhinosurgical team was organized at University Department of ENT, Head & Neck Surgery, Zagreb University School of Medicine and Zagreb University Hospital Center in Zagreb, who have developed the idea of a novel approach in head surgery. This computer aided functional endoscopic sinus microsurgery has been named 3D-C-FESS. The first 3D-C-FESS operation in Croatia was carried out at the Šalata University Department of ENT, Head & Neck Surgery in a 12-year-old child inflicted gunshot wound in the left eye region (Figure 4).

Status: gunshot wound of the left orbit, injury to the lower eyelid and conjunctiva of the left eye bulb. Massive subretinal, retinal and preretinal hemorrhage. The vitreous diffusely blurred with blood. The child was blinded on the injured eye. Six years after the 3D C-FESS surgery, the status of the left eye was completely normal, as well as the vision, which was normal bilaterally.

With due understanding and support from the University Department of ENT, Head & Neck Surgery, Zagreb University Hospital Center, and Merkur University Hospital, the scientific research rhinosurgical team from the Šalata University Department of ENT, Head & Neck Surgery organized and successfully conducted the first distant radiologic-surgical consultation (teleradiology) within the frame of the 3D-C-FESS project. The consultation was performed before the operative procedure between two distant clinical work posts in Zagreb (Šalata University Department of ENT, Head & Neck Surgery and Merkur University Hospital) (outline/network topology). In 1998, and on several occasions thereafter, the team conducted a number of first tele-3D-computer assisted operations as unique procedures of the type not only in Croatia but worldwide[1–3,6,15]

Results and Discussion

We have designed a complete lossless image compression algorithm that incorporates CBP predictor, contextual error modeling described in this paper and arithme-

TABLE 1
MEDICAL IMAGES – COMPLETE COMPRESSION RESULTS

Image	CALIC (bps)	JPEG-LS (bps)	JPEG 2000_R (bps)	CBPC (bps)
CR chest	2.35	2.39	2.52	2.27
CT abdomen	2.27	1.89	2.59	1.92
CT brain	1.24	1.29	1.42	1.10
CT limb	2.21	2.34	2.38	2.17
MR head 1	4.27	4.44	4.47	4.18
MR head 2	4.44	4.62	4.71	4.33
MR knee	4.98	5.08	5.11	4.92
angiography	3.70	3.67	3.97	3.62
RTG colon	3.21	3.20	3.45	3.10
Mean	3.18	3.21	3.40	3.07

CALIC – context-based adaptive lossless image coder,
CBPC – classification and blending predictive coder

tic coding. We have named it Classification and Blending Predictive Coder (CBPC). Table 1 shows the results of our CBPC coder compared with the results of popular lossless coders for our test set of medical images shown in Figure 5[16,17].

Those images are grey level images with 8 bits *per* pixel precision. The first column shows the bit-rates of the Context-Based, Adaptive, Lossless Image Coder (CALIC) algorithm, the second column the JPEG-LS results, and the third column shows the results of JPEG 2000 lossless compression that uses reversible wavelet transform[18]. The CBPC outperforms all other coders resulting in the best average bit rate with comparable complexity (Figure 5).

Conclusion

The results obtained with our proposed compression algorithm are encouraging. Average telecommunication and storage costs are cut to 1/3 compared to old fashioned plain systems. After testing the algorithm on a reduced set of images we have opened the possibility to apply the same to 3D models and other images that are used in new operation procedures such as images from Figure 6. As we know, the use of the latest program systems enables development of 3D spatial models (Figure

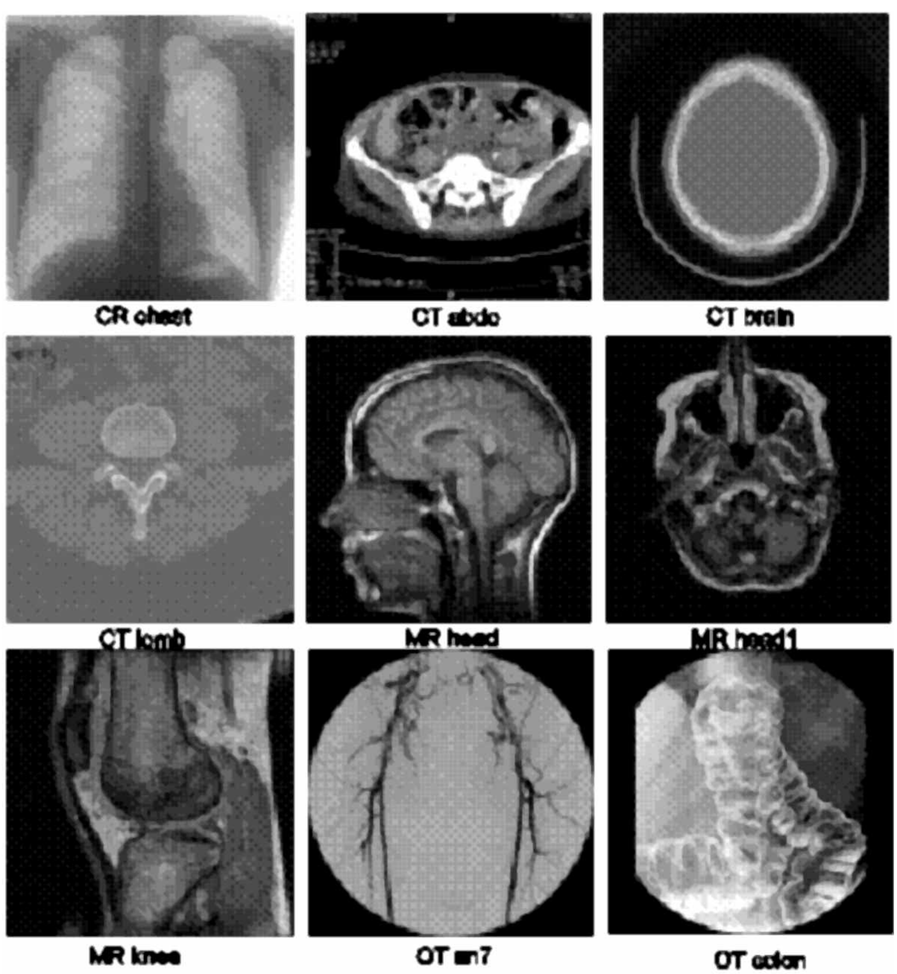

Fig. 5. Test set of medical images.

Fig. 6. Set of medical 2D and 3D images.

6), exploration in various projections, simultaneous presentation of multiple model sections and, most important, model development according to open computer standards (Open Inventor). Such a preoperative preparation can be applied in a variety of program systems that can be transmitted to distant collaborating radiological and surgical work sites for preoperative consultation as well as during the operative procedure in real time[16] (telesurgery). For realistic Tele-3D-CAS surgery as well as for appropriate simulations it is necessary for the computer to generate at least 30 such images *per* second, which imposes strong requirements to computer processing power[15]. By applying our proposed algorithm we can enable those procedures to be performed and to be performed more efficiently. Every model of the anatomy and/or pathology in medical applications will enable simulation of changes that the tissue undergoes when compressed, stretched, cut, or palpated.

The proposed approach of modeling the image as composed of regions with a mixture of dominant and nondominant properties has been shown to be efficient for lossless image compression. On the other hand, it should be noted that the increase in compression performances comes with the increase in computational complexity. Our predictor is moderately more complex than predictors used in contemporary lossless compression algorithms such as CALIC and JPEG-LS. We believe that our proposed predictor is less complex than the predictors that can be found in newer proposals for lossless compression of images and are based on the least squares approach[13]. Also, the complexity of the predictor proposed can be tuned for both goals: better compression and faster time by changing the parameters described earlier. Those parameters can be set on an image basis. The lossless compression method proposed can be easily incorporated into a more general medical image storing and retrieval system.

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APLIKACIJA NOVE METODE KOMPRESIJE MEDICINSKIH SNIMAKA BEZ GUBITAKA, KORIŠTENJEM PREDIKCIJE I KONTEKSTUALNOG MODELIRANJA

S A Ž E T A K

Provođenje tele-3D računalom potpomognutih zahvata kao i druge telemedicinske procedure često zahtjevaju najveću moguću kvalitetu medicinskih snimki i videa. Nažalost, takve vrste podataka su uvijek vezane uz visoke telekomunikacijske troškove i troškove pohrane, koji ponekad sprječavaju širu uporabu ovih procedura. Ovdje predstavljamo novi algoritam za kompresiju bez gubitaka medicinskih snimki, koji je od velike pomoći u smanjenju troškova. Glavni doprinos ovog rada je poboljšanje već poznatih modela. Pokazali smo da je ovaj pristup primjeren za kompresiju medicinskih slika. Rezultati dobiveni predloženim načinom kompresije su vrlo ohrabrujući i pobijaju nekoliko dobro poznatih načina kompresije bez gubitaka. Predloženi prediktor se također može koristiti i u drugim aplikacijama za obradu slika, kao što je segmentiranje i ekstrakcija slikovnih područja.