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Elimination of white Gaussian noise in arterial phase CT images to bring adrenal tumours into the forefront

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ABSTRACT

Dynamic Contrast-Enhanced Computed Tomography (DCE-CT) is applied to observe adrenal tumours in detail by utilising from the contrast matter, which generally brings the tumour into the forefront. However, DCE-CT images are generally influenced by noises that occur as the result of the trade-off between radiation doses vs. noise. Herein, this situation constitutes a challenge in the achievement of accurate tumour segmentation.

In CT images, most of the noises are similar to Gaussian Noise. In this study, arterial phase CT images containing adrenal tumours are utilised, and elimination of Gaussian Noise is realised by fourteen different techniques reported in literature for the achievement of the best denoising process. In this study, the Block Matching and 3D Filtering (BM3D) algorithm typically achieve reliable Peak Signal-to-Noise Ratios (PSNR) and resolves challenges of similar techniques when addressing different levels of noise. Furthermore, BM3D obtains the best mean PSNR values among the first five techniques. BM3D outperforms to other techniques by obtaining better Total Statistical Success (TSS), CPU time and computation cost. Consequently, it prepares clearer arterial phase CT images for the next step (segmentation of adrenal tumours).

1. Introduction

Image Denoising is important in medical image analysis and constitutes the first part before the segmentation/feature extraction process. In medical image analysis, CT images are generally corrupted with Gaussian noise or Poisson noise (similar to Gaussian) as defined in literature studies (Sun et al., 2013; Andria et al., 2013; Al-Ameen and Sulong, 2014). Therefore, techniques have been developed to eliminate the Additive White Gaussian Noise (AWGN) to obtain better quality CT scans.

In the literature, remarkable studies have been performed to eliminate AWGN from benchmark images. Foi et al. (2004) performed image deconvolution of benchmark images (Lena, Pepper, Boats) by combining Local Polynomial Approximation (LPA) with the Intersection of Confidence Intervals (ICI). As a result, the Anisotropic LPA-ICI technique obtained better PSNR values compared with peer studies in the literature. Elad and Aharon (2006) designed an Adaptive Dictionary technique based on K-Singular Value Decomposition (K-SVD) using sparse and redundant representations. In their study, Adaptive Dictionary was compared with Discrete Cosine Transform (DCT) based Dictionary (DCT Dictionary) and Globally Trained Dictionary. Adaptive Dictionary generally achieves higher PSNR values than other dictionary-based approaches for AWGN denoising in benchmark images. Dabov et al. (2007) developed the Block-Matching and 3D Filtering (BM3D) algorithm using concepts of 3D transform, shrinkage, grouping and block-wise operations. In their study, Gaussian noise elimination of benchmark images was achieved with remarkable performance for different standard deviations. Foi et al. (2007) designed the Pointwise Shape-Adaptive DCT (SA-DCT) algorithm inspired by the LPA-ICI technique. In their study, SA-DCT successfully denoised both grey-scale and colour benchmark images corrupted with different noise levels. Kumar et al. (2010) compared Median and Wiener filters on denoising of Gaussian noise in Flowertitlee images. According to the results, the Wiener filter exhibited higher PSNR values in addition to reduced MSE rates. Zoran and Weiss (2011) combined the Expected Patch Log Likelihood (EPLL) with Gaussian Mixture Model (GMM) and obtained the EPLL-GMM model. In trials, EPLL-GMM typically outperformed Learned Simultaneous Sparse Coding (LSSC), K-SVD and BM3D algorithms on AWGN denoising in benchmark images. Deledalle et al. (2011) introduced three dictionary-based techniques that differ according to the training algorithms employed, including Principle Component Analysis (PCA). These dictionaries included Patch-based Global PCA (PGPCA), Patch-based Local PCA (PLPCA)

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and Patch-based Hierarchical PCA (PHPCA). For denoising AWGN in benchmark images, the best PSNR values were obtained with PLPCA, but PGPCA exhibited a slower operation time compared with PLPCA and PHPCA. Knaus and Zwicker (2013) designed the Dual Domain Image Denoising (DDID) algorithm, which involves Short Time Fourier Transform (STFT) and Bilateral filters for different domains. For AWGN denoising in benchmark images, DDID generally acquired better PSNR values than the BM3D algorithm with a standard deviation of "25". Yang et al. (2015) generated a technique (LASSC) that uses a low-rank model containing Singular Value Decomposition (SVD) for elimination of coloured noise. In their study, the LASSC algorithm performed denoising and deblurring tasks efficiently on the tests with benchmark images.

In the literature, studies of noise elimination in different types of medical images have been reported. Herman and Davidi (2008) used Total Variation Minimization (TV-minimizing) to suppress the noise in CT images. TV-minimizing obtained more remarkable results than Norm-minimizing on small number of projections for reconstruction of brain images including brain tumour. Jiao et al. (2008) eliminated non-stationary Gaussian noise from low-dose CT sinograms using Stationary Wavelet Transform (SWT). SWT outperformed general smoothing filters and wavelet-based approaches in elimination of noise by preserving the edges in low-dose CT images. Matrecano et al. (2010) compared BM3D, VisuShrink and BayesShrink methods in the elimination of AWGN from Micro Computed Tomography (microCT) images. In conclusion, BM3D outperformed others and advanced to the forefront for the elimination of Gaussian noise on microCT images. Chen et al. (2011) sought to eliminate quantum noise and artefacts elimination from abdominal low-dose CT images. For this purpose, Weighted Intensity Averaging over Large-scale Neighbourhoods (WIA-LN) was used, and parameter values were arranged until optimum conditions were met. In another study by Chen et al. (2012), noise and artefact elimination from thoracic low-dose CT images was performed using Artefact Suppressed Large-scale Nonlocal Means (AS-LNLM). The Dictionary Learning-based Low-Dose CT (DL processed LDCT) technique was proposed by Chen et al. (2013). This technique outperformed LDCT, Standard-Dose CT (SDCT) and LNLM-based LDCT methods in noise and artefact elimination from abdominal CT images. In another study by Chen et al. (2014), noise elimination was performed using Artefact Suppressed Dictionary Learning (ASDL) for sinograms and abdominal CT images. As a result, ASDL obtained better results than AS-LNLM, LCDT and SCDT methods. Yang and Lee (2015) used hidden Markov models, contourlet transform and noise estimation for elimination of noise modelled as a combination of Poisson-Gaussian distributions. According to trials on fluorescence microscopy images, proposed technique outperformed other methods by obtaining reliable PSNR values. Chen et al. (2017) employed the Convolutional Neural Network (CNN) and realised noise elimination from low-dose CT images. As a result, CNN achieved better performance than ASD-POCS, BM3D and K-SVD algorithms for the elimination of Poisson noise in low-dose CT images.

Beside of noise elimination, an important area is artefact elimination which constitutes another subject in CT imaging. In CT images, there can be already artefact or the denoising algorithms can cause artefacts according to the used methodologies. For this purpose, the literature studies touching upon this subject can be considered (Chen et al., 2011, 2012, 2013, 2014).

As noted in literature, various studies assume the noise in CT images as Gaussian or Poisson, whereas a few studies consider this noise to be Quantum or Poisson-Gaussian. In this study, we examine the Gaussian noise given that it occurs in CT images. In addition, Poisson noise and the derivatives of Poisson originate from Gaussian noise. The dynamic CT images used contain high-level noise due to the poor adjustment of *radiation dose* vs. *noise*. In the first part of experiments, arterial phase CT images are corrupted with different levels of AWGN. In the second part, the elimination of the entire noise in the image is performed using state-of-the-art denoising methods. For this purpose, fourteen popular and efficient techniques were assessed for the elimination of Gaussian noise from benchmark images. Arterial phase Dynamic CT images containing adrenal tumours are used, and techniques are processed to remove the noise for a clearer CT image that will be used in our future work (about segmentation of adrenal tumours).

This study differs from other studies based on three novel points:

1. First investigation of denoising on specified (*arterial*) phase dynamic CT images
2. Examination of denoising around a specified ROI (*adrenal tumours*) in CT images
3. The most detailed comparison of denoising of Gaussian noise in CT images

The remainder of this paper is organised as follows. In Section 2, medical images, their features and the best algorithm among the fourteen methods are explained briefly in a comprehensive manner. In Section 3, we present the experimental results from the method comparison of AWGN denoising from CT images containing adrenal tumours. Herein, comparisons are performed using the PSNR metric based on literature reports and its efficiency (Deledalle et al., 2011; Knaus and Zwicker, 2013; Yang et al., 2015). In addition, a visual representation is presented to demonstrate the efficiency of the best algorithm. Also CPU times and computation costs of the first five techniques are examined to find the best one. Concluding remarks are provided in Section 4.

2. Materials and methods

The aim of this study is to prepare clearer CT images for use in the segmentation of adrenal tumours. In this study, we sought to achieve image denoising from arterial phase CT images that contain unilateral and bilateral adrenal tumours. For this purpose, AWGN is applied to images with different standard deviations, and 14 different methods are processed to remove the noises at different levels.

2.1. The dataset and its features

The dataset consists of arterial phase CT images given that this phase reveals adrenal tumours more explicitly than other phases (venous, pre-contrast, etc.). For instance, adrenal adenomas have lower attenuation values than that of nonadenomas after contrast infusion, and this situation is explicit in arterial phase. Thus, adrenal tumours can be differentiated and characterized better (Kumar et al., 2008). Therefore, this paper studies on arterial phase CT images as being first in the literature on denoising of the whole abdomen and of the ROI around adrenal tumours. However, these images are corrupted with different levels of noises, which prompted us to identify an adaptive denoising algorithm.

The image dataset was obtained from the Medicine Faculty at Selcuk University and labelled by a radiologist of Radiology Department. CT images were provided by *SIEMENS SOMATOM Definition Flash CT*. In this device, the reconstruction package is *Advanced Modeled Iterative Reconstruction* (ADMIRE). This reconstruction package presents the newest generation in Iterative Reconstruction using the industry's first raw-data-based iterative reconstruction (SAFIRE). With the use of ADMIRE, thick slices are reconstructed with a natural image impression even from ultra-low dose scans. In ADMIRE, the SAFIRE algorithm improves the image quality, level