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Artificial Systems Can Complement Human Vision in Medical Imaging

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Abstract

Texture analysis is an emerging field; and it is just beginning to integrate with radiology. Carrying out research with thousands of images can be overwhelming, without an effective and efficient sorting algorithm. The aim of this experiment was to develop a sample selection-elimination protocol for a large research project seeking to compare fetal 1.5- tesla versus 3-tesla magnetic resonance images. Firstly, we had to find optimal methods for image selection. In a compiled database of 1.5-tesla and 3-tesla images, we began by manually selecting sequences based on discernible-anatomical structures (ventricle, thalamus, grey matter, white matter). Then 1.5-tesla and 3-tesla image batches were categorized into two groups based on gestational age (i.e. first group: 20-28 week; second group: 29 week). The final stage was sample elimination by variance and by real bit-depth – that is the actual stored bits which correlate with the measured mean, not the expected mean derived from allocated bits reported in the image metadata. Though both 1.5-tesla and 3-tesla images were formatted as 16-bit digital imaging and communications in medicine, a maximum of 12 and 16 stored bits were measured in 1.5-tesla and 3-tesla respectively. This finding was crucial for fair selection and therefore ideal for assessment of the quality of 1.5-tesla versus 3-tesla – rather than simply relying on visual appearance. Stored bits were constant in both gestational groups of the same magnetic resonance modality but not variance.

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Artificial intelligence can further enhance sorting of images for comparative studies. Despite the current constraints and limitations, we recommend further feasibility studies, software development, clinical trials and eventually more substantial integration of "radiomics" (radiology and computer science) in medical practice.

keywords: texture analysis; computer-assisted radiology; media cybernetics; radiomics; hugues gentillon; mazda; artificial intelligence; differential diagnosis; computational visual cognition.

1. Introduction

In digital imaging, "bit" is a term referring to the number of shades of grey in an image [1,2]. Combination and primary filtration of three greyscale shades produce RGB color images (red, green, blue). Large number of studies have been published in the field of radiology comparing quality of different imaging modalities. Many of which solely rely on visual appearance on a computer monitor. As a result, difference is not obviously visible — when a 16-bit Digital Imaging and Communications in Medicine (DICOM) is degraded to an 8-bit Bitmap (BMP), for example. The limitation of such primitive methods is that the human eye actually sees much less details than 2^8 x 2^8 x 2^8 = 256 x 256 x 256 = 16,777,216 tonal possibilities [3,4,5,6,7]. In an image, each pixel is a possibility. For instance, a 16-bit RGB formatted image has 2^{16x3} = 281 trillion pixel values [8]. How much more details does the human eye actually perceive on a 281-trillion pixel LCD — when in reality it cannot even discriminate the full spectrum of 16,777,216 textural possibilities? Contrary to what reading between the lines might suggest, these points are introduced not really to compare the human eye with computer vision — but rather to show the need for complementary vision. To complicate the debate further, not every pixel always contains true image data. For example, a compressed CT image with 12-bit depth stored in 2 bytes (16 bits) digital container is visually lossless [9]. Unoccupied pixels are padded with data which are not part of the actual image (i.e. "padding bits") [9,10,11,12]. The latter argument leads us to consider measurement of "real bit depth" — i.e. stored bits in DICOM as primary-parametric tool of selection and exclusion. Some readers might argue that information about bit values can simply be obtained from the image metadata (DICOM tag, in this case). However, an image encoded in a 16-bit wrapper does not necessary contained 16 bits of captured information (Figure 1). Such imaging discrepancies may not be readily obvious without proper algorithm, image storage/transfer, editing techniques and information extraction.

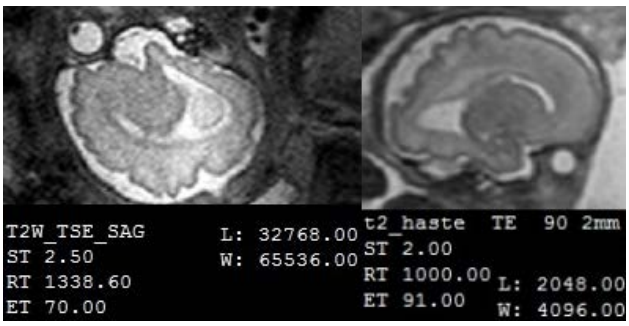

Figure 1: Magnetic Resonance Imaging: left: 1.5T=212; right: 3T=216 | Both images are wrapped in 16-bit DICOM container, but more stored-bit values were higher in 3T images.

2. Methods

In this experiment, we used both manual and digital sorting techniques prior to bit depth measurement. Before delineating the entire process, it is necessary to orient readers by defining texture analysis and state the aspects that we are pursuing in this research.

2.1. Appearance-versus-quantification

The terminology used in this experiment may immediately stimulates the mind to comprehensively perceive only the primitive aspects of texture – i.e. any structural approaches limited to human vision – such as surface's roughness, smoothness, spatial variation in pixel intensities, macroscopic appearance, pictorial representation on histogram or boxplot, etc. It is not readily understood that texture analysis also seeks to translate visual appearance into numerical parameters [13,14,15]. In this research, we are primarily interested in "feature extraction" – that is the intuitive quantification of perceived qualities of a surface. Feature extraction is perhaps the single most crucial stage of texture analysis with artificial systems (hardware/software). It is due to the fact the results obtained from feature extraction can be subsequently used as building blocks of ulterior stages (e.g. texture discrimination, texture classification, object shape determination, etc.) [16].

2.2. Computer-assisted radiology

Magnetic resonance imaging (MRI) units are promising tools in medicine — as they can be used for early detection of diseases and to increase curability and survival rate [17,18,19]. They come in different scanning powers and can produce images with high resolution and lots of details. Their Image quality and differential power can be enhanced with a variety of contrast agents, from commonly known gadolinium to novel nanoparticles. In the contexts of this research, we foresee the use of the terminology of "computer-assisted radiology" – not in the sense that a radiologist just uses a computer to look at an image and postulate a diagnosis – but in the sense that an artificial system (computer vision) makes preliminary diagnosis for re-interpretation or final diagnosis with confirmation by a radiologist. Identification of limitations in a system (artificial or human) does not necessarily means that other systems deprived of such limitations are better. While such a tendency is a conventional wisdom in society, that is not the intended focus of this research. To put the aim of this research into its ultimate perspective, we reiterate that we rather envision artificial systems as a complementation to human vision in imaging and diagnostic radiology.

2.3 Feature Extraction

In this research, we used artificial intelligent software package developed and patented by the B11 project under the umbrella of COST (Cooperation in the Field of Scientific and Technical Research). COST is a multi-disciplinary cooperation founded in 1998 by a group of inter-governmental institutions and experts in areas such as medicine, physics, computer science, artificial intelligence, cybernetics, et al. The B11 project aimed at developing quantification methods of texture analysis for medical applications. A COST software package containing MaZda version 5.0 and B11 version 3.3 was licensed to us via collaboration with Technical

University of Lodz and Medical University of Lodz. MaZda and B11 are quantitative texture analysis tools. Like any software, there are limitations and room for optimization and improvements. MaZda version 5.0 does not recognize popular compressed format such as lossless JPEG in DICOM wrapper. All such DICOM files had to be uncompressed first before they can be processed in MaZda. MaZda version 5.0 can perform 8 or 12-bit but not 16-bit feature extraction. More advanced measurements were not performed. Hence, we carried out the tests with basic feature extraction (i.e. quantification of pixel quality in raw DICOM image). We wanted to be as precise and accurate as possible. Other colleagues have previously carried out similar studies with older versions of MaZda, but DICOM images were downgraded to 8-bit BMP images. In the past, 8-bit BMP format was favored because it is universally compatible across platforms. MaZda version 5.0 is capable to extract hundreds of features from an image. As mentioned earlier, most were still invaluable for the purpose of this research. Several parameters in MaZda are limited to 8-bit or 12-bit image quantification, when we wanted to extract features from images uncompressed RAW 16-bit DICOM format. This is a food-for-thought that we hope MaZda software inventors and developers will address soon, so that we can investigate other parameters in the near future.

To overcome some of MaZda compatibilities issues and fully optimize the process, a combination of computational vision software was used (Micro Dicom 0.9, Dimensions 2, Sante Dicom 4, Photoshop CS6 64-bit Extended). We compiled a database of thousands of 1.5T and 3T images by segmenting MRI sequences into individual frames. Then we began by manually selecting images based on visible anatomical structures and regions of interests (ROIs) – i.e. ventricle, thalamus, grey matter, white matter (Figure. 2). 3T sequences originated from a brand-new Philips Achieva 3.0T scanner in Matki Polki Research Institute. 1.5T sequences were captured with a Siemens Magnetom-Avanto 1.5T scanner in Barlicki University Hospital.

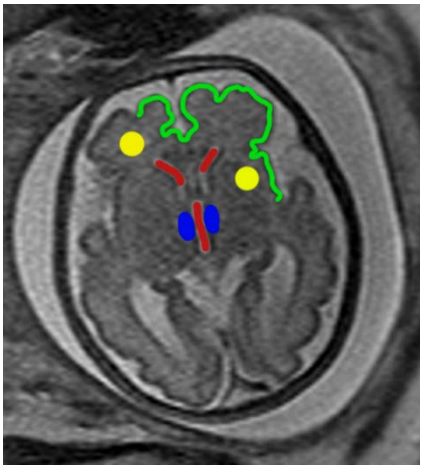

Figure 2: ROI selection

a) Red: Ventricles contain CSF, which may be colorless, cloudy or turbid – depending on mineral metabolism and/or other factors. Fluid is expected to be bright on a T2-weighted image. Thus ventricle yields the highest luminance. b) Blue: Thalamic nuclei along with basal ganglia are comprised of distinctive grey matter. These structures are expected to have low intensity signal−higher contrast than luminance on a T2-weighted image. c) Green: The cerebral cortex is an area dense in grey matter and thus is expected to appear very dark on a T2-

weighed image. It has the lowest mean (luminance) but the highest variance (contrast) on a T2- weighed image. d) Yellow: White matter appears brighter than grey matter because of its higher fat content. White matter is primarily consists of neuronal axon tract wrapped by fatty insulation (myelin) to increase signal conduction in the brain.

The first criterion was that all four ROIs must be clearly visible on the coronal plane and without artifacts. Micro Dicom was used to view and export individual DICOM frames and then simultaneously convert them to individual BMP files. Automated extraction and conversion were carried out without down-pulling – i.e. resolution was preserved. In automated export mode, conversion error occurred in DICOM dataset directories containing Lossless-JPEG formatted DICOM sequences. Folders which couldn't be automatically processed with Micro Dicom were manually decoded and converted to RAW-formatted DICOM with Sante Dicom. In few cases, we were neither able to view nor able to export individual frames. It was because DICOMDIR reference files were corrupted. We managed to manually extract some desired frames from corrupt DICOM folder with Photoshop CS6 64-bit Extended. Dimensions 2 was used to automatically exclude 3T files smaller than 448x448 and 1.5T smaller than 256x256. The vast majority of the images had the aforementioned sizes, but few did not match the size attributes in the DICOM header (tag). There flows the reason for choosing these particular sizes as exclusion criteria. Then 1.5T and 3T batches were categorized into two groups based on gestational age (i.e. first group: 20- 28wk; second group: 29wk+). The next stage was manual elimination by variance and by "real bit-depth" (stored bits); which correlates with the measured mean, not the expected mean derived from allocated bits. Extraction of bit-depth measurements was carried out semi-manually with MaZda – using macro commands (LoadImage, LoadROI, RunAnalysis).

3. Discussion

Any MRI scanners can indeed be used to create 16-bit DICOM images, and greyscale information can also be easily obtained from the file metadata or tag. Then was the measurement of greyscale properties really a waste of time? It would have been if and only if MR scanners, mode settings, transfer of image capture, encoding and storage were free from imperfections.

3.1. Reference parameters

Variance is a measurement of contrast. It is the difference in luminance and/or color that makes an object or its representation in an image or display distinguishable [20,21,22]. In other words, variance is a parameter which can be used to determine contrast variation in an image. Variance value alone is not sufficient for identification of sharp details. There was a need for an additional parameter to serve as a reference point. Therefore, the mean parameter was chosen. Mean is the average luminance of an image [21,22,23]. Measured mean must not be confused with allocated bits. They are not always equal.

3.2. Bit-depth and its correlation to dynamic range

To justify the necessity of the stored-bit sorting, we are going to intuitively explain its importance, in terms of "perceived dynamic range" (i.e. information in the image that the eye sees) and "available dynamic

range" (i.e. information in the image which is not readily visible). This concept might be difficult to grasp if one is not familiar with specialized image editing for image enhancing, information storage, hidden data recovery and extraction. Consumers of vision hardware/software who simply believe in popular marketing ploy might argue that bit-depth and dynamic range are the same thing. In reality, bit-depth and dynamic range do not necessarily equate each other [24,25,26,27]. Bit-depth can be viewed as an artificial intelligence entity with a growing desire to be smart. It can exist in different forms – e.g. capable to be stored on hard drive and magnetic tape or encoded on DNA [28,29,30,31]. On the other hands, dynamic range is the stored information (knowledge), the cybernetics along with its applied philosophies – all driven by goals. The relation between bit-depth and dynamic range is rather a conditional correlation rather than direct. Higher greyscale values do not always mean more dynamic range. Furthermore the conditions for better dynamic range are not just limited to 3T scanners having stronger magnets and being faster than 1.5T scanners. In terms of dynamic range – higher resolution, larger field of view, matrix size, slice thickness, setting mode are as important as the rest of the capturing components and process (i.e. image acquisition hardware/software and storage) [32,33,34]. Another emerging technology in radiology is used of computer to integrate patient digital photography with medical imaging examinations [35]. A simple way to demonstrate and self-prove the concept of dynamic range and its correlation to bit-depth is to use two digital photography cameras with charge coupled device (CCD) or complementary metal oxide semiconductor (CMOS) sensors: 1) take one camera with 35mm full-frame sensor and engineered for 8-bit space (e.g. 36x24mm 5D MKII) and the other about 2 x smaller sensor but 12-bit space (e.g. 15.8 x8.8mm BMCC); 2) use both cameras to capture a blown-out window image sequence during a hot sunny day and clear sky – same lens, same mode settings and same angle; 3) Use an editing software to uncompressed the sequence to 16-bit RAW or TIFF; 4) then try to recover the full blue details that the eye sees in the sky – by adjusting the exposure. In this case, the camera with the smaller sensor would outperform the camera with larger sensor. Though MRI units have different mechanics, their generated images are also subjected to bit-depth and dynamic range effects [36, 37].

3.3. Parametric versus Non-parametric

Pictorial representation on histogram or boxplot would be indeed an alternative way to visually analyze texture differences between 1.5T and 3T. However, the problem with comparing texture and intensity features by simply looking at on-screen histogram and/or boxplot is that they are both non-parametric estimates of probability distribution, based on training data – i.e. not an exact and precise representation of the reality but can still produce very low false results with proper techniques [38,39]. For example, MaZda and Photoshop CS6 64-bit Extended can both generate histogram. 12, 14, 16 and higher bit-depth files can contain much more information than 8 bit files. Yet, when displayed on Photoshop histogram, all were scaled down to 8-bit graphical representation. Even in 16-bit mode, the software still displayed them on 8-bit scale – i.e. 0-255, not 0-65536. MaZda can also quantify discreet levels in a 16-bit image but cannot output histogram graph of any image with bit-depth higher than 8. We chose to go with parametric model because we were interested in obtaining more accurate and precise quantification of the store detail (actual anatomy). Various MaZda parameters have been used for MRI quantification, segmentation and thus texture analysis [40,41,42]. The drawbacks with parametric investigation is that it demands more tedious and time-consuming processes. Apart from resolution and coronal plane, we had to further sort the images based on sequence type.

Furthermore T2-weighted images were retained to optimally differentiate normal from abnormal tissues. Samples showing advance pathologies (hydrocephalus, malformations) were subsequently excluded. Then T1 and PD images were excluded because of different shading of grey. The final batch had 144 x 3T DICOM, 144 x 1.5T, 144 x 3T BMP, and 144 x 1.5T BMP files.

4. Results

The findings showed that allocated bits were constant in both 3T and 1.5T (Figure. 5). Though both 1.5T and 3T were 16-bit DICOM formatted, maximum 12 and 16 stored bits were measured in 1.5T and 3T respectively. (Figure 3-5) This finding was crucial for further selection and thus assessment of the quality of 1.5T vs. 3T, rather than simply relying on visual appearance. Stored bits and variance were comparable between gestational groups for images having the same MR modality and similar mode settings. (Figure 3-5) In this experiment, the selected 1.5T images had constant stored-bit value (4095), while the 3T images had slightly variable values (dataset is stored online: doi:10.17632/jjwfwcsdk7.1).

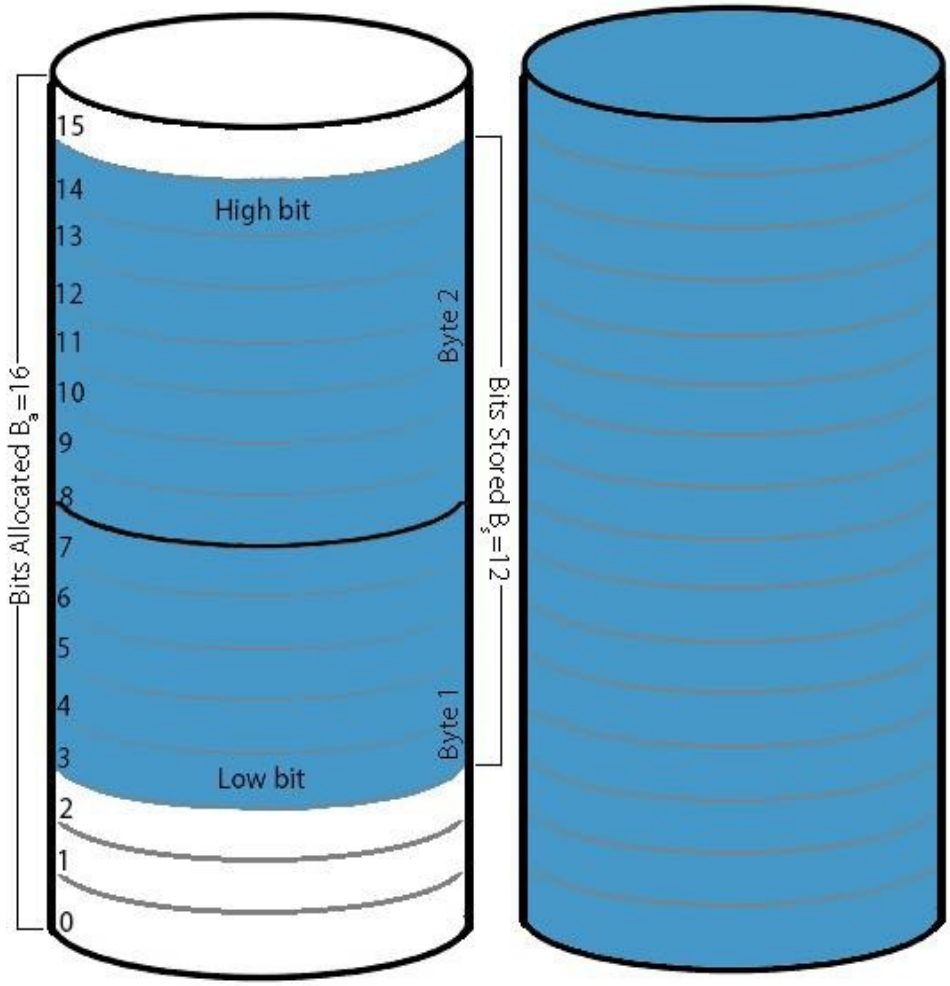

Figure 3: Stored bits: 1.5T (left), 3T (right)

The difference in stored-bit values is the effect of the encoding mode: 1.5T images were 16-bit Lossless

constant JPEG DICOM and had to be uncompressed to variable RAW DICOM to facilitate processing in MaZda – with all other parameters remaining unchanged. Stored bit was re-measured, and all the values were still the same. 3T images were natively 16-bit uncompressed variable RAW DICOM.

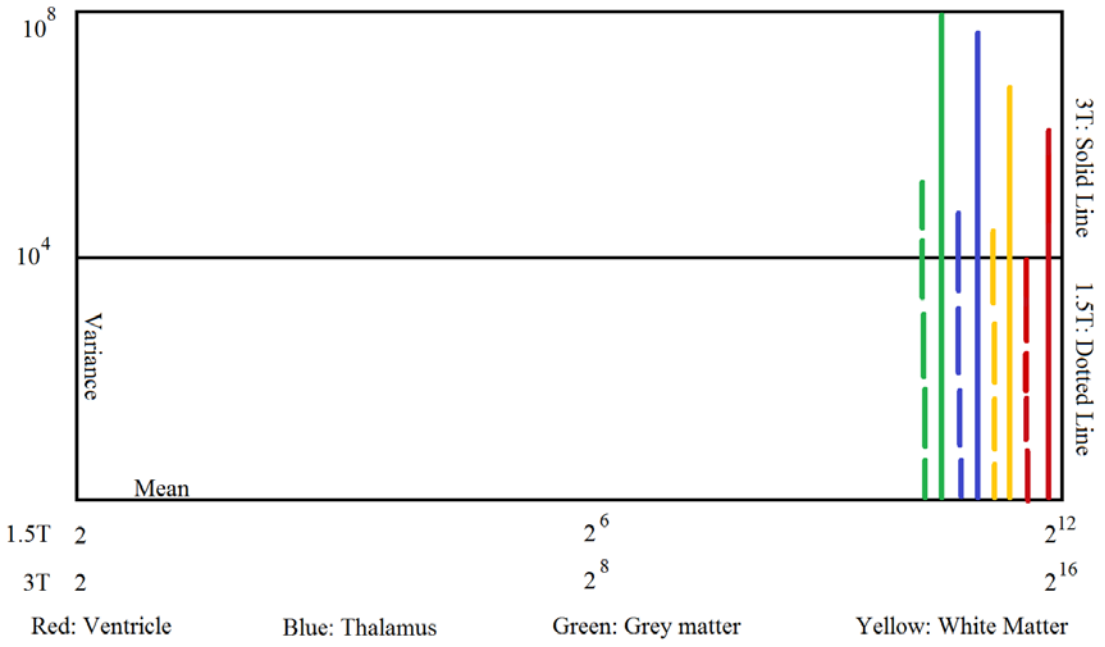

Figure 4: Group 1: 20-28wk

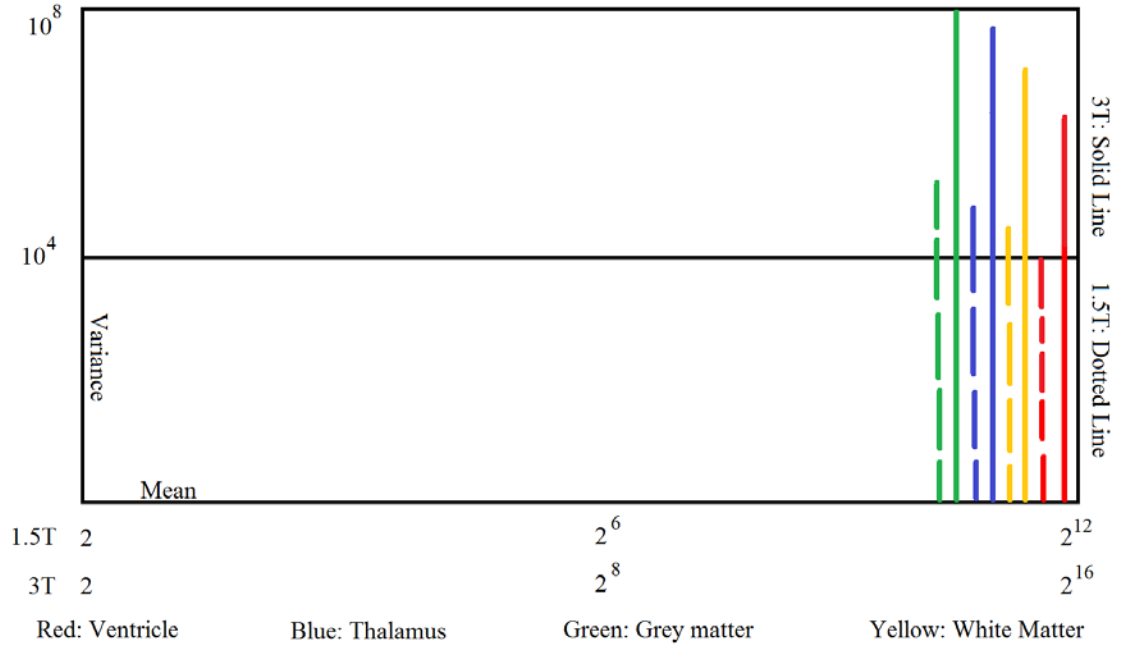

Figure 5: Group 2: 29wk+

5. Conclusion

Computational algorithm of visual texture segregation can further enhance sorting of DICOM images for comparative studies.

5.1. Constraints, Limitations, and Assumptions

At this stage, our goal was to explore the feasibility and technicality of the hypothetical ideas being tested. Hence, the study was not designed as a controlled clinical trial. Direct interaction with patients was not granted by the sponsored hospitals. Therefore, samples were assumed to be randomly collected during routine examination.

5.2. Recommendations

COST should consider to further develop, update and upgrade B11/MaZda software to facilitate accommodation of high-resolution biomedical imaging research, diagnostic studies, cross-comparison and performance studies with radio-technicians, radiologists and other physicians — and eventually qualification for registration of full-scale clinical trials.

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Ethics, Consent & Permissions

Agreement number: 3/2011 - concluded on December 6, 2011, between the experimenter (Hugues Gentillon), research supervisor (Ludomir Stefańczyk) and rector of Medical University of Lodz (Radzisław Kordek), Faculty of Biomedical Science - Post-graduate research in Diagnostic Imaging and Radiotherapy. Consent for publication of these data was obtained. Furthermore all data from human participants were anonymized as per consent agreement. Informed Bioethics Committee Approval Number: RNN/213/13/KE, JULY 16, 2013. If you have any questions regarding the decision please include the above number and date in your letter. Send correspondence to: THE BIOETHICS COMMITTEE OF THE MEDICAL UNIVERSITY OF LODZ Al. Kościuszki 4, 90-419 Łódź, tel. 0 785 911 596, 42 272-59-05, fax 42 272-59-07

Competing Interests

The author declares that there might be unforeseen academic/institutional competing interests — which the author himself is not aware of. Nevertheless, this research and its results were carried out independently and thus not endorsed by and in no way influenced by the inventors/patent owner of the MaZda / B11 software and neither financed nor encouraged by COST. Hence it is not intended to be a promotion for COST.

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