

**Research Article** 

## The Intensity-Curvature of Human Brain Vessels Detected with Magnetic Resonance Imaging

Carlo Ciulla<sup>1\*</sup>, Ustijana Rechkoska Shikoska<sup>1</sup>, Dimitar Veljanovski<sup>2</sup>, Filip A. Risteski<sup>2</sup>

<sup>1</sup>University of Information Science & Technology, "St. Paul the Apostle", Partizanska B.B., Ohrid, 6000, Republic of Macedonia <sup>2</sup>Department of Radiology, General Hospital 8-mi Septemvri, Boulevard 8<sup>th</sup> September, Skopje, 1000, Republic of Macedonia

#### Abstract

The intensity-curvature term is the concept at the root foundation of this paper. The concept entails the multiplication between the value of the image pixel intensity and the value of the classic-curvature (CC(x, y)). The CC(x, y) is the sum of all of the second order partial derivatives of the model polynomial function fitted to the image pixel. The intensity-curvature term (ICT) before interpolation  $E_0(x, y)$  is defined as the antiderivative of the product between the pixel intensity and the classic-curvature calculated at the origin of the pixel coordinate system (CC(0, 0)). The intensity-curvature term (ICT) after interpolation  $E_{IN}(x, y)$  is defined as the antiderivative of the product between the signal re-sampled by the model polynomial function at the intrapixel location (x, y) and the classic-curvature. The intensity-curvature functional (ICF) is defined as the ratio between  $E_0(x, y)$ and  $E_{IN}(x, y)$ . When the ICF is almost equal to the numerical value of one ('1'),  $E_0(x, y)$  and  $E_{IN}(x, y)$  are two additional domains (images) where to study the image from which they are calculated. The ICTs presented in this paper are able to highlight the human brain vessels detected with Magnetic Resonance Imaging (MRI), through a signal processing technique called inverse Fourier transformation procedure. The real and imaginary parts of the k-space of the ICT are subtracted from the real and imaginary parts of the k-space of the MRI signal. The resulting k-space is inverse Fourier transformed, and the human brain vessels are highlighted.

**Keywords**: Magnetic resonance imaging; inverse Fourier transformation procedure; intensity-curvature term; k-space.

#### Introduction

#### The Literature

Taking advantage of the magnetic susceptibility of deoxyhemoglobin, at ultra-high field (UHF) MRI offers the possibility to image the vasculature of the human brain (Christoforidis *et al.*, 1999). The localization and the

identification of the human brain vasculature is therefore tight to changes in the susceptibility of the human brain tissues. The MRI technique called Susceptibility Weighted Imaging (SWI) which is based on gradient echo scans (T2\* imaging) combined with unwrapped high-pass filtered phase images, provides the MRI images with contrast enhancement sufficient to image the vasculature, to enhance

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#### \*Corresponding author

Carlo Ciulla,

University of Information Science & Technology, "St. Paul the Apostle", Partizanska B.B., Ohrid, 6000, Republic of Macedonia Email: carlo.ciulla@uist.edu.mk, cxc2728@njit.edu

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white/gray matter contrast, to enhance water/fat contrast, to identify iron (Haacke et al., 2007) and other brain structures that are not background tissue (Haacke et al., 2004; Liu et al., 2015). Through the image processing technique called Maximum Intensity Projection (MIP), SWI is able to visualize vessel connectivity (Haacke et al., 2009), also venous structures and hemorrhages (Mittal et al., 2009). Imaging the human brain vasculature is very important when diagnosing stroke patients (Chen et al., 2010), and in such cases the diagnostic protocol comprises of the following techniques: (i) contrast-enhanced MRI, (ii) MR angiography, (iii) cerebral angiography, (iv) transcranial Doppler, and (v) Single Photon Emission Computed Tomography (SPECT) (Christoforidis et al., 1999). Fluid Attenuated Inversion Recovery (FLAIR) MRI is a viable technique for the identification of hyper-intense vessels which might trigger stroke in the human brain (Kamran et al., 2000). In recent years, the use of SWI has been extended to MR venography using the shift in resonance frequency between the venous vessel and the surrounding tissue. The resonance shift is caused by paramagnetic deoxyhemoglobin located in veins (Koopmans et al., 2008). Nowadays, MR venography can image small vessels of the human brain, through the use of deoxyhemoglobin as diffusible tracer (Reichenbach et al., 1997). Arterial Spin Labeling (ASL) MRI is used to label the blood water in the human brain vessels (Detre et al., 2012). Regional ASL MRI offers the advantage to measure the perfusion of the anterior and posterior circulation separately (Günther et al., 2006). MR angiography at ultra-high magnetic fields can image non-invasively the microvasculature of the brain (Cho et al., 2008).

Because of the technological efforts of the recent years, Magnetic Resonance Angiography (MRA) and contrast enhanced MRA, are among the most promising MR techniques that can be used to image the human brain vasculature (Preim and Oeltze, 2008; Sakuma, 2011). The MRA signal is detected because of the difference in radiofrequency excitation existing between stationary saturated venous blood protons and incoming non saturated blood protons (Miyazaki and Lee, 2008). Post-processing is necessary in order to make MRA available to clinical routine and it comprises of cerebrovascular segmentation and vessels delineation. The combination of the Gaussian kernel used for filtering and the Hessian of the Gaussian image as the derivative operator is the basis of the vesselness technique, which is used to improve vessel delineation (Sato et al., 1998; Frangi et al., (1998); Frangi, 2001). Moreover, recent research reports cerebrovascular segmentation through the fusion of intensity and vesselness using fuzzy rules (Forkert et al., 2011). To assess the coronary anatomy is necessary in order to diagnose several diseases and is nowadays possible through the use of both Computed Tomography (CT) and MR Angiography (Post et al., 1996). A recent study concerned with the diagnosis of coronary artery disease (CAD), compares conventional coronary anatomy performed with CT and Magnetic Resonance Imaging (MRI) as opposed to conventional coronary angiography (CAG), and finds CT more accurate than MRI (Schuetz *et al.*, 2010).

## The Motivation of the Study

The intensity-curvature term is defined as the product between the image pixel intensity and the sum of all of the second order partial derivatives (with respect to the dimensional variables) of the model function fitted to the image pixel. Such sum is called classic-curvature (Ciulla et al., 2015). The motivation of the present study originates from the evidence that some polynomial model functions have the property by which there exists striking similarity between the intensity-curvature terms (ICTs) before interpolation and after interpolation (Ciulla et al., 2017). This similarity makes the ratio between ICTs (which is called intensity-curvature functional (ICF)) very close to the numerical value of one ('1') across the all spatial extent of the image, and therefore makes the ICF useless. In such cases, despite the loss of information due to an unusable ICF, the ICTs ( $E_0(x, y)$  and  $E_{IN}(x, y)$ ) can still be utilized (Ciulla et al., 2017). This paper presents the study of the behaviour of the ICTs calculated from two polynomial model functions called B32D and G42D (Ciulla et al., 2017). The study is carried out through a novel approach, which makes it possible to delineate human brain Magnetic Resonance Imaging (MRI) detected vasculature. The approach is based on the inverse Fourier transformation of the difference between the k-space of the MRI and the kspace of the intensity-curvature term (ICT). The difference comprises of: (i) the real part of the k-space of the MRI minus the real part of the k-space of the intensity-curvature term; and (ii) the imaginary part of the k-space of the MRI minus the imaginary part of the k-space of the intensitycurvature term. After the difference is calculated, the real and imaginary parts are inverse Fourier transformed, and thus the reconstructed signal is obtained.

## **Materials and Methods**

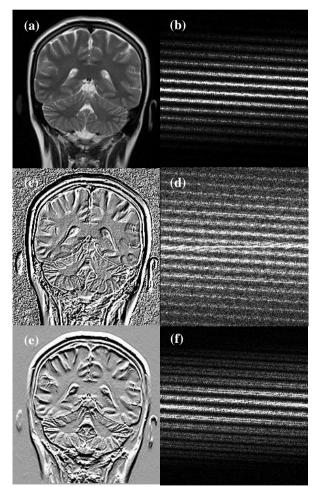
Magnetic Resonance Imaging of one healthy subject was recorded with the pulse sequences parameters indicated in Table 1, where: TE is the Time to Echo; TR is the repetition time; FOV is the field of view. The magnet was the Magnetom Essenza, Siemens with strength 1.5 T. The measurement protocol was the localizer. The MRI scanning procedures were conducted in compliance with the ethical standards set by the General Hospital 8-mi Septemvri, Skopje – Republic of Macedonia, which is the institution where the subject was studied. Informed consent was properly administered prior to the MRI scanning procedure. The mathematics of the two model polynomial functions (B32D and G42D) utilized in this research and the math procedures necessary to calculate the intensity-curvature terms are reported elsewhere (Ciulla *et al.*, 2017). This paper reports on the applications the ICTs and the use of the ICTs by means of the inverse Fourier transformation procedure.

MRI acquisition	Fig. 1	Figs. 2, 3, 4, 5	
TE	96 msec	2.59 msec	
TR	5050 msec	7 msec	
FOV	204 x 250	280 x 280	
Pixel matrix size	196 x 320	410 x 512	
# of slices	28	18	

### Results

#### The Intensity-Curvature Functional

The intensity-curvature functional (ICF) of the bivariate cubic polynomial model termed B32D, and the ICF of the bivariate cubic Lagrange polynomial model termed G42D, is a ratio which value is near the numerical value of one ('1') overall the full spatial extent of the image.



**Fig. 1:** MRI in (a). (b) K-space of (a). (c) The intensity-curvature functional of (a). (d) K-space of (c). (e) The high pass filtered MRI. (f) K-space of (e). The bivariate linear function was fitted to the MRI data because its ICF is an image which pixel intensity values are not equal to one ('1').

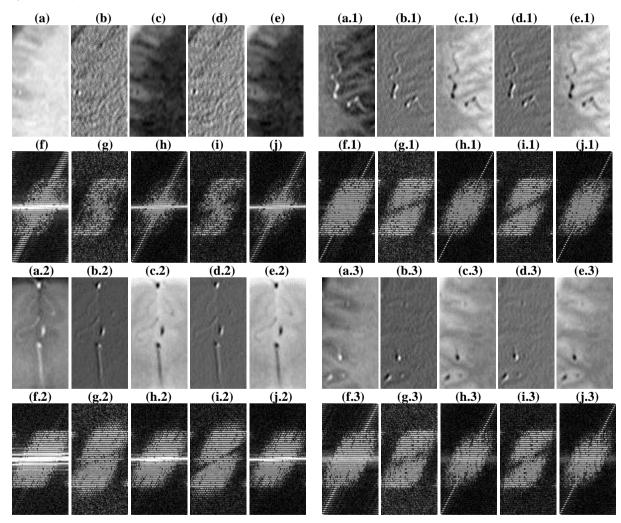
This happens when the option provided by the program in order to process the signal is: 'n' (normalize). Note that the aforementioned behaviour of the ICF is not common to other mathematical functions, such as for instance the bivariate linear model function. It is due to acknowledge that the ICF is similar to MRI high pass filtered signal and as such it is useful as an alternative high pass filter of the MRI signal (Ciulla *et al.*, 2016). It is also due to report, as Fig. 1 shows, that the k-space of the MRI high pass filtered signal is different from the k-space of the ICF (Ciulla *et al.*, 2017). Thus, the ICF and the MRI high pass filtered signal are not the same (Ciulla *et al.*, 2017). The next section of the paper presents the study of the human brain vasculature with the ICTs.

# The Study of the Intensity-Curvature Terms with Applications to MRI Human Brain Vasculature

The MRI images were cropped and divided in two classes: control zones (5) and regions of interest (ROIs) (20). For each control zone and for each region of interest, the ICTs were calculated when the equations of two polynomial model functions were fitted to the MRI data. Thus, for a selected control zone or region of interest, four ICTs were calculated. Fig. 2 shows four cases.

Each case comprises of ten pictures: one MRI image, four ICTs images and five k-space images. Each case is labelled with letters: (a) through (j); and with letters and numbers (to distinguish among cases located in the same figure: for instance (a.1) through (j.1)). Figs. 2 and 3 show: (i) the MRI zone studied (a); (ii) the  $E_0(x, y)$  and the  $E_{IN}(x, y)$  calculated from the bivariate cubic polynomial model (B32D) (see (b) and (d) respectively); (iii) the  $E_0(x, y)$  and the  $E_{IN}(x, y)$ calculated from the bivariate cubic Lagrange polynomial model (G42D) (see (c) and (e) respectively). Figs. 2 and 3, show in (f), (g), (h), (i) and (j) the k-space of each of (a), (b), (c), (d) and (e) respectively. Careful selection of the control zones and regions of interest is assured because the choice of the control zones display only cortical surface, whereas the regions of interest where chosen so to make sure that the image was inclusive of vasculature structures also. In Figs. 2 and 3, both  $E_0(x, y)$  and  $E_{IN}(x, y)$  were calculated using the bivariate cubic polynomial model (B32D) and they have filtering effect on the MRI. It is visible in the pictures that the cortical surface is flattened and the vasculature is highlighted. Such behaviour finds confirmation in the k-space of the images. Specifically, the k-space of the MRI (a) (which is presented in (f.x)) shows additional frequencies versus the k-space in (g.x) and (i.x). Thus, in (b.x) and (d.x), the vasculature structures are isolated on a flattened cortical surface and the vasculature is well distinct (see Figs. 2 and 3). This occurrence suggests that the ICTs calculated from B32D do filter the MRI. This effect is also visible when the analysis is focused on the control zones (see Figs. 2 and 3). Note that 'x' is the image label identifier. For instance, in Fig. 2, (a.x) means: (a.1), (a.2) and (a.3). Likewise, in Fig. 3, (a.x) means: (a.1) and (a.2). The intensity-curvature terms (ICTs) of the bivariate cubic Lagrange polynomial (G42D) display an effect similar to the ICTs calculated from the bivariate cubic polynomial model (B32D). Such effect suggests that the ICTs calculated from the polynomial model termed G42D do filter the MRI also. To see the aforementioned effect, look at the k-space in (g.x) and (i.x) in Figs. 2 and 3, and compare the k-space images to the k-space image calculated from the MRI, which is displayed in (f.x). Some frequency components are missing in (g.x) and (i.x). Although, visible in the ICTs images calculated from the bivariate cubic Lagrange polynomial model (G42D), the filtering effect is more accentuated in the ICTs calculated from the bivariate cubic polynomial model (B32D) (see (b.x) and (d.x) of Figs. 2 and 3). Overall, the results show that the ICTs have

imaging capabilities that make them suitable to highlight (delineate) the human brain vasculature imaged with MRI. In Fig. 4, the difference between the k-space of the MRI and ICT is calculated by the subtraction of the real and imaginary parts of the k-space. Which is, the real part of the k-space of the MRI, minus, the real part of the k-space of the intensity-curvature term. And, the imaginary part of the k-space of the intensity-curvature term. After the difference is calculated, the real and imaginary parts obtained through it, are inverse Fourier transformed, and thus the reconstructed signal is obtained. (a.3), (a.5), (a.7), (a.8), (a.9) Are control zones.



**Fig. 2:** Control zone selected in the human brain MRI: (a). The intensity-curvature terms before interpolation: calculated from B32D and presented in (b), calculated from G42D and presented in (c). The intensity-curvature terms after interpolation: calculated from B32D and presented in (d), calculated from G42D and presented in (e). (f) The k-space of (a). (g) and (h) The k-space of (b) and (c). (i) and (j) The k-space of (d) and (e). Vasculature in the human brain MRI: (a.1), (a.2), (a.3). The intensity-curvature terms before interpolation: calculated from B32D and presented in (b.1), (b.2) and (b.3); calculated from G42D and presented in (c.1), (c.2) and (c.3). The intensity-curvature terms after interpolation: calculated from B32D and presented in (d.1), (d.2) and (d.3); calculated from G42D and presented in (e.1), (e.2) and (e.3). (f.1), (f.2), (f.3) The k-space of (a.1), (a.2), (a.3), respectively. The k-space of (b.1), (b.2), (b.3) and (c.1), (c.2), (c.3) is in (g.1), (g.2), (g.3) and (h.1), (h.2), (h.3), respectively. The k-space of (d.1), (d.2), (d.3) and (e.1), (e.2), (e.3) is in (i.1), (i.2), (i.3) and (j.1), (j.2), (j.3), respectively. All images have pixel matrix size 57x113.

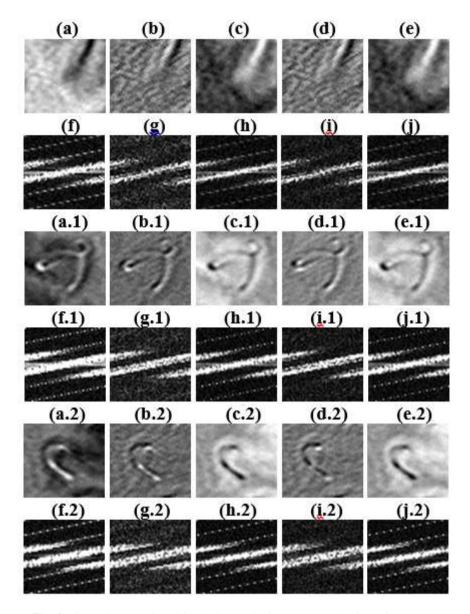
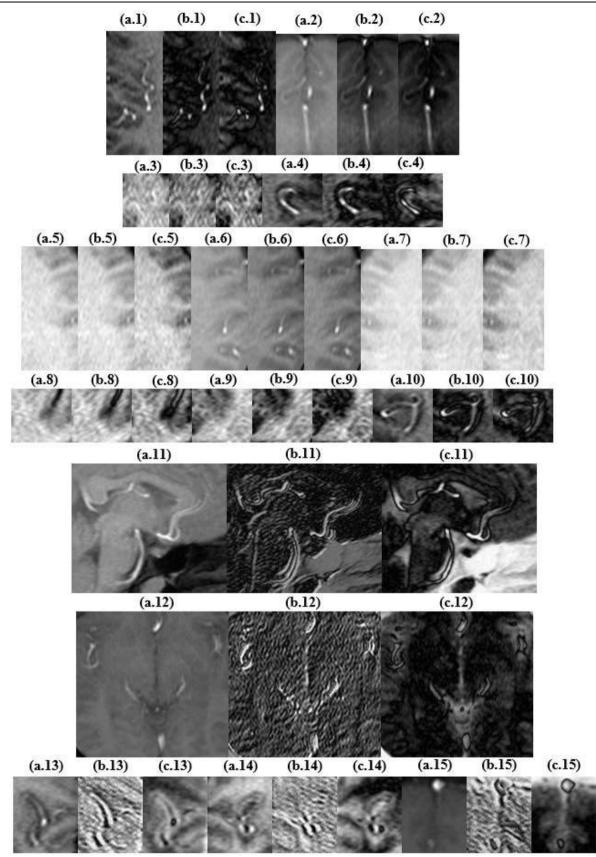
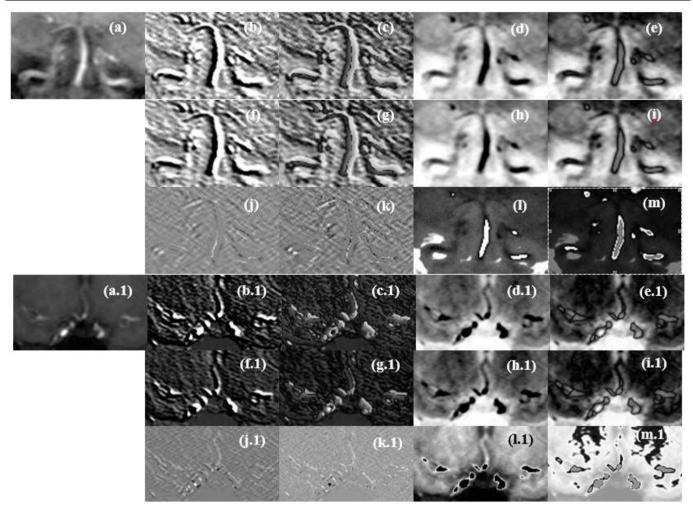


Fig. 3: Control zone selected in the human brain MRI: (a). The intensity-curvature terms before interpolation: calculated from B32D and presented in (b); calculated from G42D and presented in (c). The intensity-curvature terms after interpolation: calculated from B32D and presented in (d); calculated from G42D and presented in (e). (f) The k-space of (a). (g) and (h) The k-space of (b) and (c). (i) and (j) The k-space of (d) and (e). Vasculature in the human brain MRI: (a.1), (a.2). The intensity-curvature terms before interpolation: calculated from B32D and presented in (b.1) and (b.2); calculated from G42D and presented in (c.1) and (c.2). The intensity-curvature terms after interpolation: calculated from B32D and presented in (d.1) and (d.2); calculated from G42D and presented in (e.1) and (e.2). (f.1), (f.2) The k-space of (a.1), (a.2), respectively. (g.1), (g.2) and (h.1), (h.2) The k-space of (b.1), (b.2) and (c.1), (c.2), respectively. (i.1), (i.2) and (j.1), (j.2) The k-space of (d.1), (d.2) and (e.1), (e.2), respectively. All images have pixel matrix size of 56x51.



**Fig. 4:** MRI images in: (a.1), (a.2), (a.3), (a.4), (a.5), (a.6), (a.7), (a.8), (a.9), (a.10), (a.11), (a.12), (a.13), (a.14), and (a.15). The reconstructed signal after inverse Fourier transformation of the difference between the k-space of the MRI and the k-space of the intensity-curvature term (calculated from the polynomial model function termed B32D) is presented in (b.1), (b.2), (b.3), (b.4), (b.5), (b.6), (b.7), (b.8), (b.9), (b.10), (b.11), (b.12), (b.13), (b.14) and (b.15). The signal reconstructed after inverse Fourier transformation of the difference between the k-space of the MRI and the k-space of the intensity-curvature term (calculated from the polynomial model function termed B42D) is presented in (c.1), (c.2), (c.3), (c.4), (c.5), (c.6), (c.7), (c.8), (c.9), (c.10), (c.11), (c.12), (c.13), (c.14), (c.15).



**Fig. 5:** MRI images: (a), (a.1). The ICT before interpolation  $(E_0(x, y))$  calculated from the polynomial model function termed B32D is presented in (b) and (b.1), and the reconstructed signal is presented in (c) and (c.1). The ICT before interpolation  $(E_0(x, y))$  calculated from the polynomial model function termed G42D is presented in (d) and (d.1), and the reconstructed signal is presented in (e) and (e.1). The ICT after interpolation  $(E_{IN}(x, y))$  calculated from the polynomial model function termed B32D is presented in (f) and (f.1), and the reconstructed signal is presented in (g) and (g.1). The ICT after interpolation ( $E_{IN}(x, y)$ ) calculated from the polynomial model function termed B32D is presented in (f) and (f.1), and the reconstructed signal is presented in (g) and (g.1). The ICT after interpolation ( $E_{IN}(x, y)$ ) calculated from the polynomial model function termed G42D is presented in (h) and (h.1), and the reconstructed signal is presented in (i) and (i.1), respectively. Difference images: (b) minus (f) is in (j); (b.1) minus (f.1) is in (j.1); (c) minus (g) is in (k); (c.1) minus (g.1) is in (k.1); (d) minus (h) is in (l); (d.1) minus (h.1) is in (l.1); (e) minus (i) is in (m); (e.1) minus (i.1) is in (m.1). The images (a) through (m) have pixel matrix size 118x77. The images (a.1) through (m.1) have pixel matrix size 152x85 and to the purpose of the presentation in the figure, they were resized maintaining the aspect ratio.

The results presented in Fig. 4 show highlight of the vessels, which is featured mostly by the suppression of the tissue and the enhancement of the vessels visibility (the ICTs were all 'before interpolation':  $(E_0)$ ). Thus, in essence, the procedure has the effect of filtering out the MRI images. Table 2 reports the pixel matrix size of the MRI images and the ICTs images presented in Fig. 4. The research presented in this paper contributes two additional domains where is possible to observe and study the human brain vasculature: the ICTs. However, the main contribution of the study is to delineate the vasculature of the human brain through the use of the ICTs in the inverse Fourier transformation procedure. The filtering effect is visible through the analysis of the kspace presented in Figs. 2 and 3. The ICTs calculated from the bivariate cubic polynomial model (B32D) make the filtering effect on the MRI more accentuated than the filtering effect obtained when fitting the bivariate cubic Lagrange polynomial model (G42D).

**Table 2:** Regions of interest (ROI(s)) and pixel matrix size of the MRI images.

ROI(s)	1/5/6	2/7	3
Pixel matrix size	53x116	57x113	43x50
ROI(s)	4/8/9/10	11	12
Pixel matrix size	56x51	183x154	181x175

In the top row and the third row from the top are reported the label of the triplet of images identifiable in Fig. 4 with: (a.x), (b.x), (c.x). For instance, the MRI image label '1' identifies the images (a.1), (b.1) and (c.1) (see Fig. 4), and the ROI is the MRI presented in (a.1). In the second row and the bottom row are reported the corresponding pixel matrix size of the images.

The filtering effect is also visible in the ICTs images where the vasculature is highlighted and the rest of the brain cortex is moderately flattened (see (b.x) and (d.x) in Figs. 2 and 3). The filtering effect of the ICTs is also visible in Figs. 4 and 5. In Figs. 4 and 5, the k-space of the ICT is subtracted from the k-space of the MRI, the resulting k-space is inverse Fourier transformed, and the outcome is again to highlighting the human brain vessels.

## Discussion

When studying the properties of SWI imaging, is possible to characterize the magnetic susceptibility versus the vessel size, to create novel venograms on the basis of susceptibility maps (Haacke *et al.*, 2010; 2015), and to map the  $T2^*$ relaxation time (Denk and Rauscher, 2010). A growing number of research groups have developed techniques providing quantitative measures of magnetic susceptibility (Liu et al., 2015; Wang and Liu, 2015). The use of MRI techniques like MR Angiogram (MRA), and MR Venogram (MRV) at ultra-high field show increased susceptibility (Von Morze et al., 2007; Bae et al., 2010) versus 3T, and increased capability to distinguish between arteries and veins (Duvernoy et al., 1981). The increased susceptibility obtained with SWI at 7T makes it possible to see changes in image contrast and is a consequence of low oxygenated venous blood (Deistung et al., 2008). MRI post-processing provides the detection of veins with diameter smaller than a pixel (Reichenbach et al., 1997). The importance of the determination of the vessel size has been addressed and studied within the context of tumor MRI and the feasibility to distinguish the vascular size in normal tissue and tumor had been reported (Hsu et al., 2009). Following contrast agent administration, which yields to change of contrast in MRI images between tissue and vasculature of the human brain, MRI techniques using the susceptibility change have been able to determine quantification of vessel dimensions. More specifically, the ratio between the changes in transverse relaxation rate constants of the spin echo R2 and of the free induction decay  $R_{2}^{*}$  (prior and after the injection of the contrast agent), embeds a portion of susceptibility difference between vessels and brain tissue (Tropres et al., 2001) and allows the quantitation of the vessels size. Similarly, Vessel Size Imaging (VSI) (Kiselev et al., 2005) is an MRI technique which bases the quantitative assessment of the vessel caliber on the relation between: (i) contrast-enhanced relaxation rate R<sup>\*</sup><sub>2</sub> of the free induction decay, and (ii) the relaxation rate  $R_2$  of the Spin Echo (SE). The combination of the two pulse sequences: Gradient Echo and Spin Echo, along with the injection of the contrast agent had been used in animal studies in order to quantify estimates of micro-vessel density (Jensen et al., 2006). For a review of traditional filtering techniques, which is inclusive of performance comparison of the detection of tubular structures, the reader is referred to work reported elsewhere (Xiao et al., 2013). The literature reports the use of: (i) the Gaussian and/or the Rectangular filtering kernel and (ii) the derivative operator (the Laplacian and/or the Hessian) in order to detect tubular structures and also human vessels from clinical images (Xiao et al., 2013). The

contribution of this piece of research is the use of the intensity-curvature terms with the inverse Fourier transformation procedure. This signal processing technique is novel and is capable to delineate and highlight human brain vasculature detected with MRI.

## Conclusion

The use of the intensity-curvature concept is what makes possible to delineate the human brain vasculature in MRI. The concept entails merging the image pixel intensity with the sum of second order partial derivatives of the model function fitted to the image pixel. From the concept descends the image processing techniques called intensitycurvature terms (ICTs). The motivation of the study emanates from the fact that for some model polynomial functions the intensity-curvature functional is close to the numerical value of one ('1') across the full spatial extent of the image. In the specifics, for the model polynomial functions B32D and G42D, this happens when the option provided by the program in order to process the signal is: 'n' (normalize). In such cases the study of the ICTs is consequential. The ICTs are used in this research within the context of the inverse Fourier transformation procedure. The k-space of the ICT (real and imaginary parts) is subtracted from the k-space of the human brain MRI (real and imaginary parts). The resulting k-space is inverse Fourier transformed and the resulting reconstructed signal show clear delineation of the vasculature. The results reported in this paper indicates that the highlight of the vasculature through the inverse Fourier transformation is of relevance to diagnostic biomedical imaging.

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