**MRI scanner attribution from its pattern noise**

Fantini I.1, Rodrigues L.1, Rittner L.1 , Lotufo R.1

1MICLab – Medical Image Computing Laboratory, School of Electrical and Computer Engineering, UNICAMP

**Introduction:** The usage of medical images has grown as well as the studies looking for methods that automatically detect diseases from them. Research centers collect images from different sites and specific data can be lost. When an image set presentsundesirable characteristics which can jeopardize the study, like high noise, the original equipment attribution become necessary. This work aims to propose a method to identify the Magnetic Resonance (MR) equipment that generate the image, based on the image noise and the fact that normally sensors leave a mark in the image identified as source pattern noise.

**Materials and Methods:** T2-weighted Fluid Attenuated Inversion Recovery (FLAIR) brain MR images were acquired in a 3T scanner using same protocol, with slice thickness of 3mm, as 2D type and axial. There are two MR sensors model Discovery MR750 from GE Medical Systems configured with TR = 9700, TE = 141, TI = 2200 and image size 256x256, and one model Triotim from Siemens configured with TR = 9000, TE = 119, TI = 2500 and image size 256x192. There were 25 exams per equipment with 48 slices each.

Each sensor leaves marks at produced images related to its hardware characteristics. These marks, commonly called residual noise, are used to identify the MR scanner by calculating the correlation between noise of the image and the scanner pattern noise. The residual noise of the image is the difference of the original image and the same image filtered by a denoising filter based on wavelet domain. The sensor noise pattern is the mean of residual noise of images from the same scanner.

Since our database has different image sizes, 9 regions of interest (ROIs) with fixed size were chosen focusing on the center of the image. The denoising filter was applied to each ROI.

The dataset was split in 20% to calculate the scanner pattern noise, 60% to train a multiclass classifier, in which each class represents one scanner, and 20% to test the final classifier. The 3-class classifier training was performed in a 5\*2-fold and no data normalization was necessary.

**Results:** Experiments were performed training SVM classifier comparing multiclass algorithms *One versus One* and *One versus All*. Also two ROIs size were compared: 32 and 64.  The *One versus All* SVM with ROI size of 32 achieved the best result, with average accuracy of 71.78% (Class1 with 68.38%, Class2 with 67.24% and Class3 with 79.81%).

**Discussion:** The presented methodology were able to perform scanner attribution, given one unknown MR image from a controlled image dataset (obtained using the same protocol, but from differente scanners). But, when using the proposed approach in a practical problem, it is possible find one that the unknown image belongs to a scanner different from those used on the training, i.e, an unknown scanner. In this case, the desired outcome from the classifier is that the sensor is not recognized. This model attribution problem is called as Open Set scenario and  was not tested, since it requires a larger dataset , containing images from a larger number of MR scanners. Also, adding ROIs from the peripheral image regions can enhance the sensor representation leading to better results.

**Conclusion:** The present work confirmed that the modeling applied to camera attribution [1] [2] can be adapted to MR scanner attribution. The smaller ROI achieved better results.

**References:** [1] J. Lukas et al., Information Forensics and Security, IEEE Transactions on, 1(2):205–214,  June 2006; [2] Filipe de O. Costa et al., Pattern Recognition Letters, 39:92 – 101, 2014.