# CT-SCANNER IDENTIFICATION BASED ON SENSOR NOISE ANALYSIS

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## ABSTRACT

Medical image processing is considered as an important topic in the domain of image processing. It is used to help the doctors to improve and speed up the diagnosis process. In particular, computed tomography scanners (CT-Scanner) are used to create cross-sectional medical 3D images of bones. In this paper, we propose a method for CT-Scanner identification based on the sensor noise analysis. We built the reference noise pattern for each CT-Scanner from its 3D image, then we correlated the tested 3D images with each reference noise pattern in order to identify the corresponding CT-Scanner. We used a wavelet-based Wiener filter approach to extract the noise. Experimental results were applied on eight 3D images of 100 slices from different CT-Scanners, and we were able to identify each CT-Scanner separately.

***Index Terms*—** Digital forensics, medical image forensics, authentication, device identification, noise pattern, sensor noise, denoise filtering, wavelet transformation, Wiener filter.

## 1. INTRODUCTION

Medical imaging has become nowadays an essential organ in the world of medicine, which refers to the techniques that can be used to have a look inside the body without need to be opened up surgically. Medical image processing by the way, has become also a common technique in the domain of image processing.

Computed tomography [1] that is also called CT-Scanner images, integrates a series of X-ray views that are taken from so many different angles to create cross-sectional images of the bones and soft tissues inside the body. The main objective of CT-Scanner images is to provide much more information than normal X-ray images. It is particularly used to provide a quick diagnosis regarding the patient situation of internal injuries. It can be used to visualize almost all the body parts and it is widely used since it provides a lot of information about the patient, the physical features and the potential disease. Information about the acquisition and device identification, generally are stored in the DICOM files [2]. DICOM file may be decomposed into two parts, meta data and raw image. Meta data is easily readable, it contains all the information about the acquired device and acquisition system, but in the absence or unauthenticated metadata, we are in crucial matter, where we are in need to identify the CT-Scanner from its raw images. Image forensics is considered an important field of research [3], that aims to validate the authenticity of images by recovering information about their history, in the presence of a non authenticated device or content modification.

In the term of digital image forensics, two basic problems are addressed: forgeries tracing and identifies the imaging device. Regarding the trace of forgeries, a lot of work is found in general digital photography [4], but in the scope of medical images and more specifically the CT-Scanners, very few work existed. In [5], the authors present the first work of digital blind forensics within the medical imaging field. They proposed a method to detect whether an image has been modified or not by general image processing operators. Even for the device identification, nothing entirely dedicated to this topic, even though there were some works about analyzing the medical image characteristics according to the acquisition parameters and device [6]. In [7], the authors proposed a method for digital camera identification from sensor pattern noise, they used a wavelet based denoise algorithm to separate the noise component. Then, they generated a reference noise pattern for the digital camera and finally, they used the correlation to match the image to its corresponding camera. The main defect in this method that is being built for the normal 2D digital images, but our basic concern is the slices of 3D medical CT-Scanner images.

In this paper, we propose a first analysis of this problem. Using a denoising algorithm we built a reference noise pattern for each device, then we identified the CT-Scanner based on the correlation between the tested slices and the reference noise pattern of each device.

The rest of this paper is organized as follows. In Section 2, we explained our proposed method for CT-Scanner identification with the denoise schema, CT-Scanner reference pattern and the identification by correlation. In Section 3, we previewed our experimental results in addition to some discussions and finally, we concluded our work with an expected future work in Section 4.

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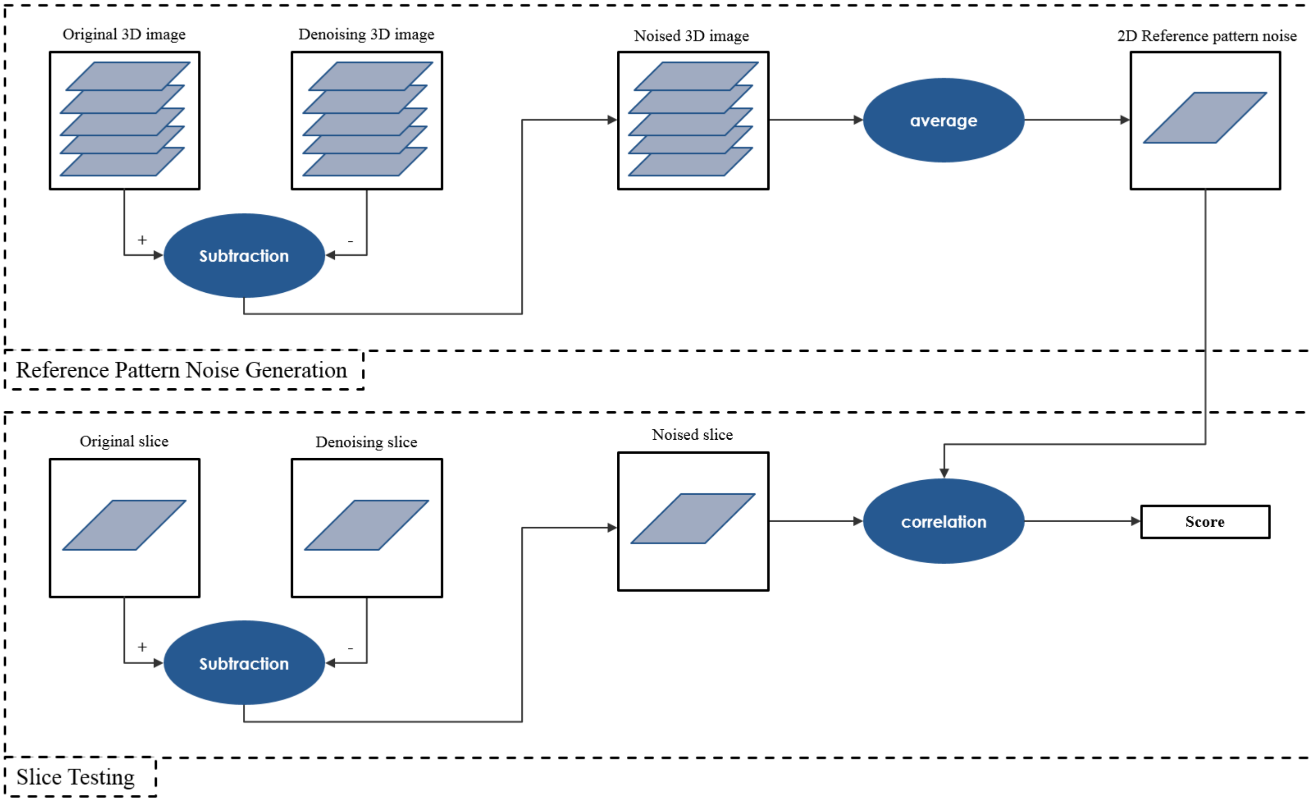


**Fig. 1**. Overview of the method.

## 2. CT-SCANNER IDENTIFICATION METHOD

The proposed method is based on the method presented in [7]. In the presence of many devices (CT-Scanners), we generated the reference pattern noise for each device as illustrated in Fig. 1. In order to identify a slice as acquired by a specific device, we applied a correlation between the noise component of this image and the reference pattern noise of each device. This image is classified as acquired by a specific device when it has the highest correlation value with its reference pattern noise as illustrated in Fig. 1. In this section we present the denoising algorithm that used to isolate the noise component, then the reference pattern noise generating and finally, how the decision of device identification is made.

### 2.1. Denoising algorithm

We applied a filter using a wavelet transform in the frequency domain and based on the proposed work in [8]. The remaining noise achieved by this specific algorithm contains the least amount of traces of the image content. Basically, this algorithm is composed of two parts, the local variance estimation of the wavelet components in the first part and denoising of these components using Wiener filter [9] in the second one as follows:

- Compute four levels of wavelet decomposition. In each level, mark out the three high frequency sub-bands that are horizontal, vertical and diagonal. For four levels of wavelet decomposition with three sub-bands in each level we have 12 sub-bands for each processed image.

- For each wavelet sub-band, based on the pixel neighborhood with four levels from the first boundary neighbors with square size of (3x3) to the fourth boundary ones with square size of (9x9), we apply the local variance estimation:

$$\hat{\sigma}^2_W(i,j) = max\left(0, \frac{1}{W^2} \sum_{(i,j)\in W*W} \left(X^2(i,j) - \sigma_0^2\right)\right), \quad (1)$$

where $W \in \{3,5,7,9\}$ refers to the neighborhood level, $X$ is the wavelet sub-band and $\sigma_0$ is an initial integer constant value that we tuned manually, $\sigma_0 \in [1,6]$.

Among the four previous values regarding the four levels of neighborhood, we select the minimum value as the estimated variance:

$$\hat{\sigma}^2(i,j) = min\left(\sigma_3^2(i,j), \sigma_5^2(i,j), \sigma_7^2(i,j), \sigma_9^2(i,j)\right). \tag{2}$$

- Denoise the wavelet sub-bands using Wiener filter, that is used to filter out noise that has corrupted a signal:

$$X_{den}(i,j) = X(i,j)\frac{\hat{\sigma}^2(i,j)}{\hat{\sigma}^2(i,j)+\sigma_0^2}, \tag{3}$$

where $X$ is the wavelet sub-band.

- Apply the inverse wavelet transformation on the denoised wavelet sub-bands to get the denoised component $F(s)$ of the original image $s$.

### 2.2. CT-Scanner reference pattern

We collected a group of images from each device, for each group we applied a denoised function to extract the denoised component, then we subtract it from the original version to extract the noise component from each slice in this group as illustrated in Fig. 2:

$$n^{(i)} = s^{(i)} - F(s^{(i)}), \tag{4}$$

where $n$ is the noise component, $s$ is the slice, $F()$ is the denoising function and $i$ is the slice number.

Then, we averaged the noise slices in one slice (2D image) that is the noise reference pattern or what is called the device fingerprint, we continue the averaging in each group to extract the device reference pattern:

$$RPN = \frac{1}{N}\sum_{i=1}^{N} n^{(i)}, \tag{5}$$

where $RPN$ is the reference pattern noise, $N$ is the number of noise slices and $n$ is the noise component.

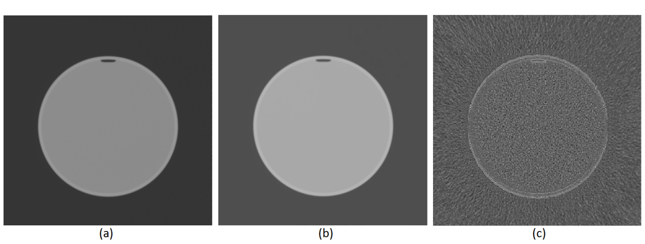


**Fig. 2**. a) Example of an original slice from Siemens 1, b) its denoised component, c) the noise component.

### 2.3. Decision by correlation

Since we have several devices and a group of images, we want to identify from which device these images were acquired. We extract the reference pattern noise for each device, extract the noise components from the group of images. These images are identified as acquired from a specific device when it has the highest correlation value with its reference pattern noise:

$$corr(n_{(i)}, RPN) = \frac{(n_{(i)} - \bar{n_{(i)}}).(RPN - \overline{RPN})}{\|n_{(i)} - \bar{n_{(i)}}\|\|RPN - \overline{RPN}\|}, \tag{6}$$

## 3. EXPERIMENTAL RESULTS

To test our proposed method we applied the experiments on eight 3D images from 3 different CT-Scanners. These images are coded in 16 bits and acquired using the same parameters (Beam energy is 120 KV, pitch value is around 1 and the slice thickness is 3 mm), each 3D image is consisted of 100 slices of 512x512 pixels. Three 3D images of phantom of calvary of an adult from Siemens 1, three 3D images of head phantom as Siemens 1 from Siemens 2 and two 3D images of skull from General Electric as illustrated in Table, 1.

**Table 1**. Experimental images.

| | Siemens 1 | Siemens 2 | GE |
|---|---|---|---|
| Content | phantom | phantom | skull |
| Nb of images | 3 | 3 | 2 |
| Nb of slices | 300 | 300 | 200 |
| Nb of slices of RPN | 120 | 120 | 120 |
| Nb of tested slices | 180 | 180 | 80 |
| Size (pixels) | 512x512 | 512x512 | 512x512 |
| Bits per pixel | 16 | 16 | 16 |
| Slice thickness | 3mm | 3mm | 3mm |
| Pixel size | 1mm | 1mm | 1mm |

In CT-Scanner, 3D images are not isotropic, we decided to work on slices, where pixels are isotropic. We decided to work on 2D slices in order to have many identification feedbacks. To create the reference pattern noise of each device, regarding each CT-Scanner, we selected 120 slices randomly, we got for each device a 3D image of 120 slices. Depending on the previous described method of RPN extraction, we extracted a reference pattern noise for each device. Fig. 3 illustrates the three references according to each device, we can notice the noise component in addition to some borders. These borders are result of the averaging operator regarding the 3D image content.

The rest of slices from each device are kept to test the CT-Scanner identification. These slices are tested with the reference pattern noise of each device. 120 slices from the General Electric, 180 slices from the Siemens 1 and 180 slices from the Siemens 2. First, we extracted the noise component from these slices according to the denoising schema, then subtract the denoised component from the original image to get an image of noise. For each noised image, we apply the correlation between these slices and the reference pattern noise of each device. To check the results, we repeated these experiments five times and we got the same result each time.

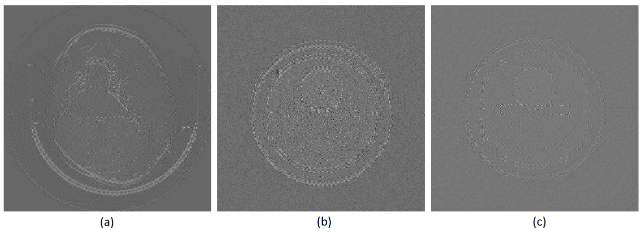


**Fig. 3**. Example of the reference pattern noise from: a) the General Electric, b) the first Siemens device, c) the second Siemens device.

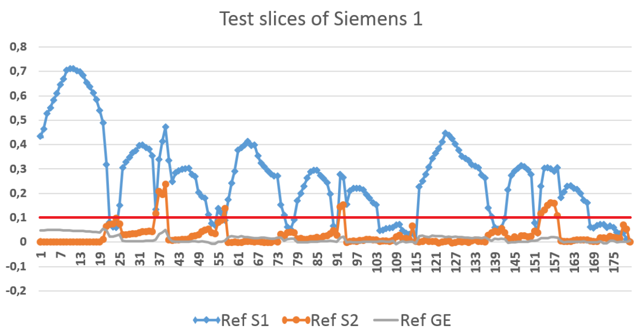


**Fig. 4**. Correlations between the tested slices of Siemens 1 and the reference noise pattern regarding each device.

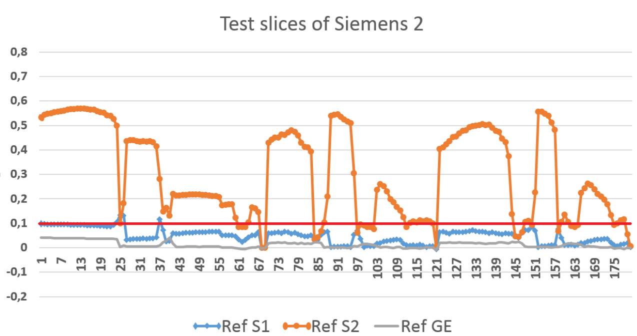


**Fig. 5**. Correlations between the tested slices of Siemens 2 and the reference noise pattern regarding each device.

From the plots of Fig. 4, Fig. 5 and Fig. 6 we noticed that the correlations between the tested slices and the reference noise pattern of the related device are classified as the highest values. It is quiet clear that the correlation between the tested image and the reference noise pattern of the device that acquire this image is always the highest. Fig. 4 illustrates the correlation between the three reference noise patterns (Siemens 1, Siemens 2 and General Electric) and the

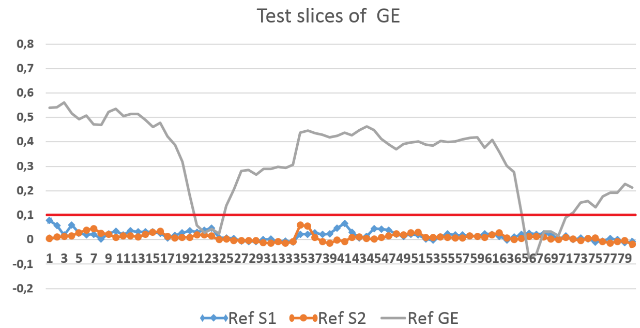


**Fig. 6**. Correlations between the tested slices of General Electric and the reference noise pattern regarding each device.

180 slices from Siemens 1. The vertical axis refers to the correlation value and the horizontal axis refers to the slice number. Regarding the vertical axis, we can notice the correlation between the reference from Siemens 1 and the tested slices of Siemens 1, almost all of these correlation values are more than 0.1, while all the other correlation values are less, that refers to the relation between this device and the tested image. So, we can consider the value 0.1 as a threshold that classifies the images being acquired by the device of this reference, except some images regarding its content, as we will see the identification percent in Table, 2. It is also the same as in Fig. 5 and Fig. 6.

**Table 2**. Identification accuracy

| | Siemens 1 | Siemens 2 | GE |
|---|---|---|---|
| Siemens 1 | 95.5 % | 3.0 % | 5.0 % |
| Siemens 2 | 4.0 % | 97.0 % | 0 |
| GE | 0.5 % | 0 | 95.0 % |

Table, 2 shows up the classification rate, when we correlated 180 slices from Siemens 1, 180 slices from Siemens 2 and 80 slices from General Electric with each device reference noise separately:

- 95.5 % of slices from Siemens 1 are classified correctly as acquired from Siemens 1, but 4.5 % of slices weren't classified correctly.
- 97 % of slices from Siemens 2 were classified correctly as acquired from Siemens 2, but 3 % of slices were not.
- 95 % of slices from General Electric were classified correctly as acquired from General electric, but 5 % of slices were not.

## 4. CONCLUSION AND FUTURE WORK

In this paper, we proposed an algorithm for medical image forensics. For the coming studies, we will work with more images and more devices, we are going to generalize our work in 3D, to study the influence of image content, to study the characteristics of the slices that give small correlation, to try to identify sub-parts of the images in the case of merging different images, to study the possibility of classifying the images that are acquired by one device but in different acquisition parameters, to analyze the reconstruction process and to study the influence of acquisition parameters. From the other hand, we are going to study the influence of image compression on the CT-Scanner identification.

## 5. REFERENCES


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