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HIGH QUALITY REAL-TIME VIDEO WITH SCANNING ELECTRON MICROSCOPE USING TOTAL VARIATION ALGORITHM ON A GRAPHICS PROCESSING UNIT

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The scanning electron microscope (SEM) is usually dedicated to taking a picture of micro-nanoscopic objects. In the present study, we wondered whether a SEM can be converted as a real-time video display. To this end, we designed a new methodology. We use the slow mode of the SEM to acquire a high quality reference image that can then be used to estimate the optimal parameters that regularize the signal for a given method. Here, we employ Total Variation, a method which minimizes the noise and regularizes the image. An optimal lagrangian multiplier can be computed that regularizes the image efficiently. We showed that a limited number of iterations for Total Variation algorithm can lead to an acceptable quality of regularization. This algorithm is parallel and deployed on a Graphics Processing Unit to obtain a real-time high quality video with a SEM. It opens the possibility of a real-time interaction at micro-nanoscales.

Keywords: denoising, GPU, nano-microscopy, real-time, SEM, total variation, video

INTRODUCTION

A light microscope is not the appropriate technology to obtain very high resolution of micro-nanoscopic objects. Indeed, it is impossible to observe a scale which is smaller than the wavelength of light. The scanning electron microscope (SEM) had a much better spatial resolution enabling the observation of these micro-nano objects. The principle of the SEM is the following: a very tight beam of electrons is focused in a raster-scan strategy over a micro-nano object and secondary electrons are detected to provide a shaded-like image of the 3-D shape of the object (Von Ardenne 1938a; 1938b). This appearance of 3-D is due to the secondary electrons which are low energy electrons that are emitted after the collision of the primary electron with the surface of the object. The most important point is that the secondary electron signal is dependent of the 3-D orientation of the surface (see Figure 1). For this reason, the resultant image looks like a shaded 3-D image of the object.

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NOMENCLATURE

GPU	Graphics 15 Processing Unit	SEM	Scanning Electron Microscope

The quality of the image obtained with a SEM is enhanced with an increasing rasterization time. In Figure 2, one can observe the evolution of the quality of the image after 0.08, 0.3, 2, 10, and 20 seconds. Micromanipulation, assembly, or physical characterization are applications that need observations in real-time. These constraints can limit the time for the acquisition of the image, meaning a quicker rasterization. And a quicker rasterization time negatively impacts the image quality.

Indeed, the electrons beam interacts with a small surface (100 nm to 5 microns) to take a sample. As the number of samples increases, the quality of the image increases in the same trend. It means that the visual quality of the restitution of the object is proportional to the time spent to scan the microscopic object (see Figure 2).

Here, we propose to create a video with different images produced by the SEM. The constraints are both, on the quality of the video and on the time to display the video. If we acquire the data at a frequency f_s, our aim is to compute a good regularized image in a time T_c inferior to $T_s = 1/f_s$. Figure 2 shows the result after only 0.08 seconds of observation. Our aim is to propose a new technique based on image processing that allows to compute a high quality image in real-time.

Our principle is to use as a reference the high quality image computed in the slowest case, and to be able to find the optimal parameters for a given regularization technique. The performances of the technique are then measured objectively. And this

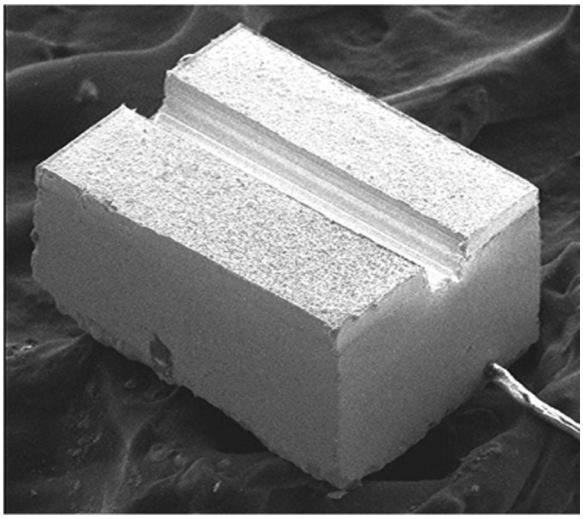

Figure 1. MagPieR is a double world champion microrobot("2 mm dash" in 2010 and"mobility challenge" in 2011, at NIST IEEE Mobile Microrobotics Challenge) from the French Institutes FEMTO-ST, ISIR and LPN.

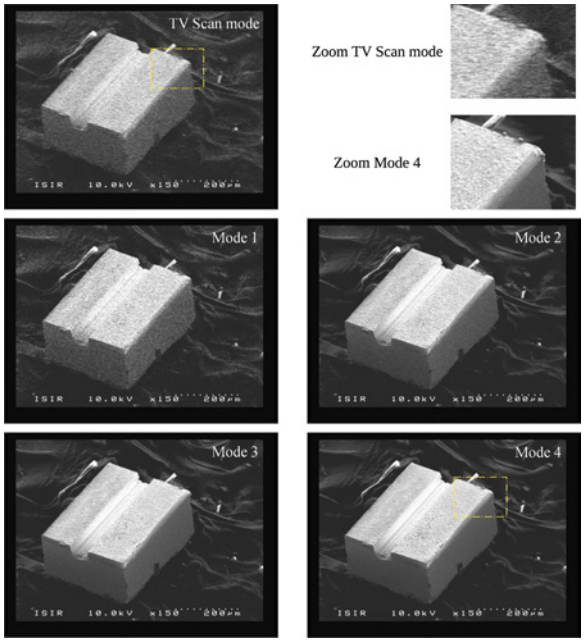

Figure 2. The TVSCAN mode and the four observation modes. The quality of the image is improving when the time of scanning increases. TVSCAN mode presents the worst quality of observation because of the high speed time for scanning (0.08 s). Mode 4 shows the best quality of observation thanks to a long scanning duration (20 s). Top right, a comparison between zoom of TVSCAN mode and mode 4 (color figure available online).

method can be used with many different techniques like gaussian filtering, median filtering, wavelet denoising (Ouarti and Peyre 2009) or gradient methods (Chambolle 2004). And the performances of these algorithms can be compared with each other.

Here, we propose a gradient method, called Total Variation, to improve the image quality. The most important feature of this algorithm of restoration is its edge preserving property. And it most important limitation is the difficulty to obtain a real-time implementation, that is the focus of this study.

MATERIALS AND METHODS

Materials

We observe with a Scanning Electron Microscope (SEM) a microscopic object at different scanning times, i.e., different level of image quality.

The Sample

The sample used is the MagPieRmicrorobot (see Figure 1). Its dimensions are $300 \times 380\,\mu m^2$ with a height $130\,\mu m$. It consists of two materials. The top is composed of a ferromagnetic layer Ni and the bottom is a piezoelectric material

(PMN-PT). It was specially designed for breaking the speed record '2 mm dash[1] at NIST IEEE Mobile Microrobotics Challenge held at ICRA2010 in Alaska (Ivan et al. 2011). MagPieR also won the 'mobility challenge' at NIST IEEE Mobile Microrobotics Challenge held at ICRA2011 in Shanghai.

The SEM

The SEM used is a Hitachi S4500. It is equipped with a cold-cathode field emission electron gun. The detector used is a secondary electron detector.[2] The Hitachi S4500 has different modes of observation, which depends on the speed of scanning. Four are currently used for observation in static mode (mode 1 to 4). A fifth one (TVSCAN mode) is a dynamic mode with a high speed of scanning (which implies a very low quality of view) and is used to look for the sample and manipulate it. These five modes are used to record the video. The quality of images or videos depend on the speed of scanning, i.e., the selected mode (see Figure 2).

- Mode 1: scan speed = 0.3 s
- Mode 2: scan speed = 2 s
- Mode 3: scan speed = 10 s
- Mode 4: scan speed = 20 s
- TVSCAN: scan speed = 0.08 s[3]

SEM Video output is a BNC output. It is linked to the PC with an USB video stick.[4] The link between the stick and the SEM is made with two adapters, a BNC/RCA male connector which is connected to an A/V Input Adapter Cable microUSB. A free commercial software[5] is used to record the video.

The SEM is set as below:

- accelerating voltage: 10kV
- extracting voltage: 6 kV
- current emission: 10 μA

EXPERIMENTAL METHODS

The video begins with a top view of MagPieR in the fourth mode. During 9 s, parameters related to SEM configuration are displayed.[6] Each mode is then observed during 20 s from mode 4 to TVscan mode (see Table 1). From time 01:49 to time 03:07, the specimen stage is tilted manually from 0° to 45° (see Figure 3) and shifted from 12,280 mm to 12,720 mm in order to keep the observed object on the field of

[1]MagPieR covers this distance in 28ms.
[2]Conventionnal secondary electrons detector Everhart-Thornley in lower position.
[3]TVSCAN fast mode : Frame averaging = 4 at 50 Hz.
[4]PCTV Hybrid Pro Stick 340e.
[5]PCTVsystems : TVCenter 6.4.0.784.
[6]Accelerating voltage, setup Working distance, position of Secondary Electrons (SE) detector.

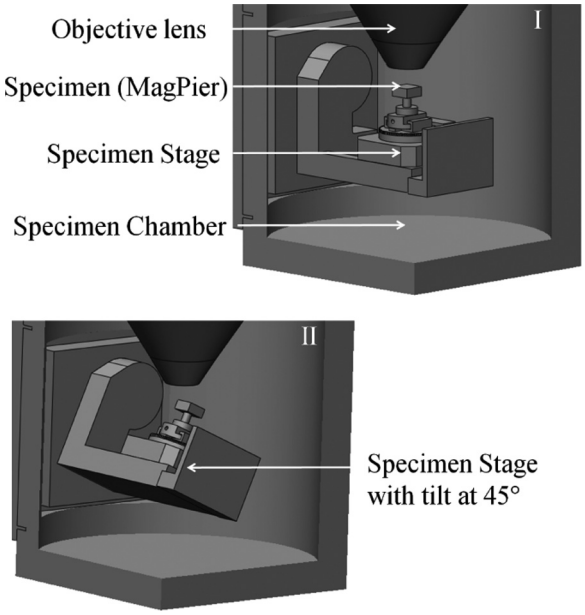

Figure 3. Cross section from inside SEM specimen chamber. Figure 1, the specimen stage with a reference position. Figure 2, the specimen stage with a tilt at 45°.

view (under the objective lens). When the stage movement is finished, each mode is observed at least 20 s from TVSCAN mode to mode 4 (see Table 1).

Quality Evaluation: PSNR

After the utilization of a denoising algorithm, what kind of method can be used to quantitatively measure the quality of the obtained results? Indeed, the subjective assessment can be interesting to judge if an image is good or not. However as a subjective judgment it is difficult to render it reliable.

In this article we choose a method to quantify the quality of image based on PSNR. The PSNR is mathematically defined as the following:

$$\mathrm{PSNR} = 10 \cdot log_{10}\left(\frac{d^2}{EQM}\right) \tag{1}$$

$$\mathrm{EQM} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}||I_o(i,j) - I_r(i,j)||^2. \tag{2}$$

With I_o and I_r the two images to compare $[mXn]$ the size of the image and d the dynamic of the image, in our case $d = 255$.

The PSNR can be regarded as a measure of distance between two images. If the comparison is made between a given image and a high quality version of this image, the PSNR can be seen as a measure of quality of the processed image. In our case, at

the beginning of the video, the same steady image was picked at different scan speed. We used the lowest scan speed of 20 seconds (i.e., highest image quality) to compute the reference image. This reference image is used to compute the PSNR. This allows us to have an objective estimation of the fluctuation and to really evaluate the performance of the algorithm while the objects in the video are steady.

Fps

In this article, we denote by frames per second (fps) the value related to the inverse of time needed by the algorithms to grab a frame, to process it, and to display it. It is an important variable, in our study, for the evaluation of the algorithms related to the computation cost of the algorithms in their parallelized version.

Regularization Method

We stored a video at 25 Hz that was the input for testing our software. Our goal was to obtain a high quality version of the video which is still as fluid to be considered as real-time.

Because of the small number of sampling, the fluctuation of the image observed can be considered as noise. The evaluation of this so-called noise is the most important step of our method.

In the case of a noisy signal: $f = u + n$, where f is the noisy signal u the denoised signal and n the gaussian noise of standard deviation σ.

The solution is the minimization of the following:

$$\frac{1}{2}||f - u||_{L_2}^2 - \sigma^2. \tag{3}$$

We proposed an edge preserving method that allows a conservation of the tridimensional structure. This method is a gradient method called Total Variation (Rudin et al. 1992; Chambolle 2004; Chambolle and Lions 1997), it is a regularization method that removes the fluctuations of the images. The principle is the minimization of the L_1 norm of ∇u, where u is the image.

Stating that the image belongs to the space of function of bounded total variation BV, it means that:

$$||\nabla \mathrm{u}||_{\mathrm{L}_1} \leq \mathrm{K}, \text{with } K \text{a constant.} \tag{4}$$

When the noise is known, the solution is:

$$\min_u \left\{ ||\nabla u||_{L_1} + \frac{1}{2}||f - u||_{L_2}^2 - \sigma^2 \right\}. \tag{5}$$

When the noise is unknown, it is equivalent to minimize as shown in the following:

$$\min_u \left\{ ||\nabla u||_{L_1} + \frac{\lambda}{2}||f - u||_{L_2}^2 \right\}, \tag{6}$$

with a lagrangian multiplier λ. The lagrangian multiplier will monitor the degree of denoising.

A key point for the algorithm is the estimation of λ which is usually proportional to the noise, the fluctuation in our case.

We propose the following procedure (Algorithm 1):

- Observation of a fix object during few seconds at the better image quality mode (mode 4).
- Computation of the restoration algorithm with different parameters values.
- Determination of the ideal parameterization of the algorithm by processing the error between our restored image and the image which has an improved quality.
- After few seconds the parameters are found and the real-time processing can be started.
- λ_0 is the initial lagrangian multiplier, maxIter the maximum number of iterations, λ^* the best lagrangian multiplier, $imag_{ref}$ is the reference image recorded in the mode 4, $imag_{noisy}$ is an image computed at the TVSCAN mode and DenIm is $imag_{noisy}$ after denoising.

Algorithm 1: Bestlagrangian multiplier

Data: λ_0, maxIter
Results: λ^*
Begin
$Imag_{ref} \leftarrow$ record(mode_4)
$Imag_{noisy} \leftarrow$ record(mode_tvscan)

For i $\leftarrow$ maxIter **down to** 0
  $DenIm_i \leftarrow$ TVdenoising($\mathrm{Imag_{noisy}}, \lambda_0\ 2^i$)
  $PSNR_i \leftarrow$ psnr($\mathrm{DenIm_i}, \mathrm{Imag_{ref}}$)
End
$i^* \leftarrow max_i\{PSNR\}$

IMPLEMENTATION

To speed up the processing time of this algorithm, we implemented it in a parallel framework using a Graphics Processing Unit (GPU). This allows a real-time computation. The GPU used in this work had 192 cores with a 1375 MHz processor clock. The algorithm was programmed with Cuda, a GPU dedicated language.

$$p^0 = 0 \tag{7}$$

$$q_{ij}^n = \mathrm{div}\left(p_{ij}^n\right) - \lambda f_{ij} \tag{8}$$

$$p_{ij}^{n+1} = \frac{p_{ij}^n + \tau\nabla\left(q_{ij}^n\right)}{1 + \tau\left|\nabla\left(q_{ij}^n\right)\right|} \tag{9}$$

$$u = f - \lambda \mathrm{div}(p^\infty) \tag{10}$$

With f, the noisy signal, λ the lagrangian multiplier, div the divergence operator, ∇ the gradient,$|.|$ the norm, τ a constant equal to $1/4$, p and q denoting intermediate variable. Each ij combination corresponds to one pixel in the initial image. On GPU, each (i, j) pixel is computed independently with this algorithm. But the algorithm is also iterative, meaning that a global loop exists that cannot be parallelized (iterations on n).

RESULTS

Our aim was to compute a regularized image based on its noisy version.

Relation Between λ and the Number of Iterations

The aim of this study is to compute a regularized version of a noisy image in real-time.

For the Total Variation algorithm, a small λ induces a more important regularization. It can be shown also that a smaller λ causes a higher number of iterations (see Figure 4).A quasi-monotonic behavior of the curve can be observed.

The convergence of the algorithm can sometime take more than 400 iterations, that is not compatible with a real-time version even with our framework. For this reason, we investigated the effect of the number of iterations on the PSNR.

Figure 5 shows the PSNR results after denoising with our algorithm in the TVSCAN condition. Each curve corresponds to a given number of iteration. The dashed line corresponds to the PSNR of the noisy version. It can be observed that an accurate choice of λ has an important impact on the quality of the denoising. Here the optimal λ^* found was 0.04. It can be already observe with this representation of the data that the number of iteration has a small effect after a given value. We compute another representation in Figure 6 to observe it more accurately. We showed for λ^* the gain of PSNR specifically related to the number of iterations. The plateau is quickly reached and the additional gain after 15 iterations is small (less than 0.30) compared to the overall gain of quality (2.4). We did not add a Figure illustrating the PSNR function of frames per second, because it would be

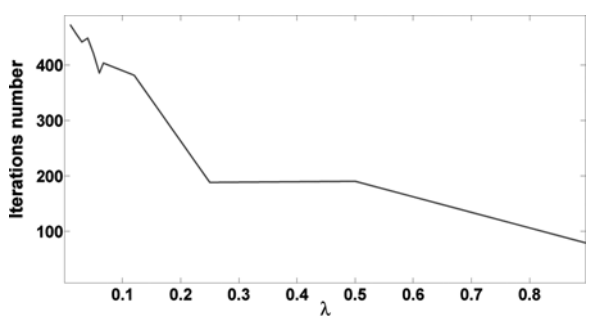

Figure 4. Relation between λ and the number of iterations for the convergence of the Total Variation algorithm. The number of iterations is increasing almost monotonously as λ is decreasing (color figure available online).

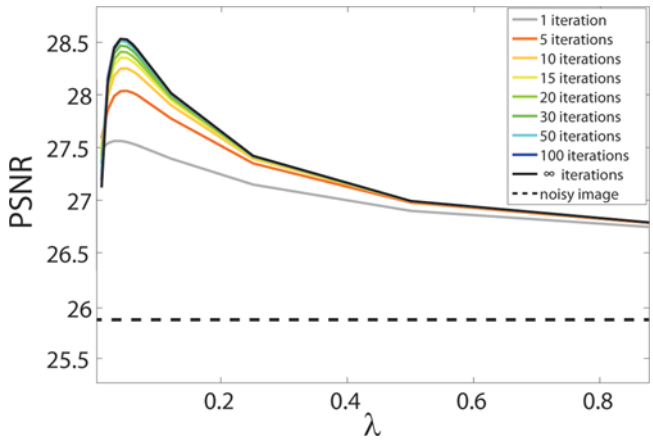

Figure 5. Evolution of the PSNR in the function of λ and in the function of the number of iterations. Each curve has a different λ. The optimal λ^* is 0.04. The dashed line represents the PSNR for the noisy image (color figure available online).

exactly the same curve than the Figure 6, one loop lasting approximately 5 milliseconds with our implementation.

SEM Video

Once the best lagrangian multiplier is obtained ($\lambda^* = 0.04$\$), the whole video can be compute using the TVSCAN mode with a scan speed of 0.08 (worst quality video). The two important variables are the PSNR and the frames per second (fps). We choose to write in real-time on the video these two variables for the"noisy" version and the regularized version.

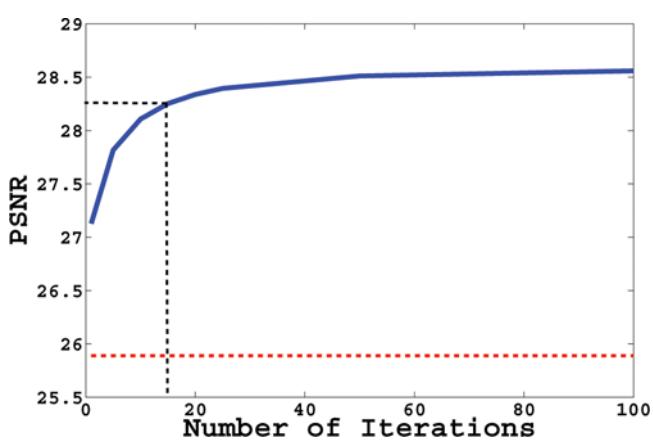

Figure 6. PSNR in the function of the number of iteration with $\lambda = \lambda^* = 0.04$. The curve reaches a plateau very quickly after 15 iterations. The dashed line represents the PSNR for the noisy image (color figure available online).

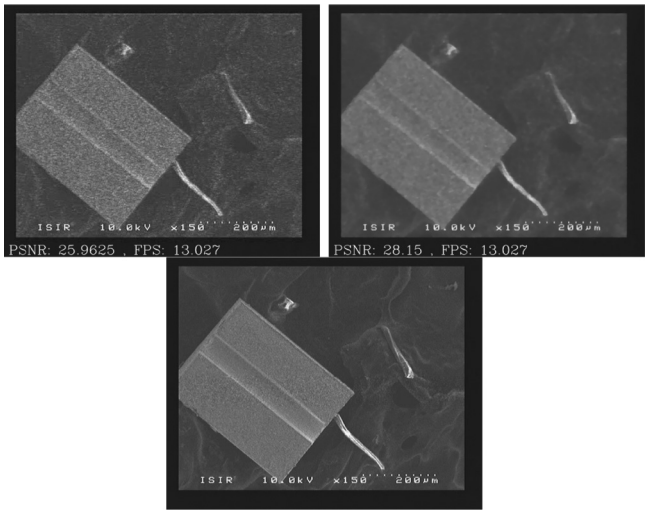

Figure 7. Noisy image real-time regularized with our technique (TVSCAN condition). (*a*) noisy image (PSNR = 25.96). (*b*) denoised image (PSNR = 28.15). (*c*) reference image for the computation of the PSNR. Fps = 13.03.

These results are shown in Figure 7. It can be shown that with 15 iterations, the video can reach 13 fps with a PSNR of 28.15 (denoting a good image quality), one loop lasting approximately 5 milliseconds. This result is different than the results of Figure 6 because we did not take the same frame. There are some small fluctuations between frames, but the result is qualitatively the same.

We showed with these results that we are able to remove the fluctuations due to the incomplete rasterization. We can obtain it in real-time. But the number of iterations needed to obtain a more denoised image do not allow for the moment to obtain a better gain in PSNR. The result obtain here: fps around 13 have to be compare to a Matlab algorithm (Chambolle 2004) were the fps was 0.034, i.e. 29 seconds to denoise one image. The fps obtained with our algorithm allows to interact with a micro-object in real-time.

The originality of our technique is to be able to quantify the denoising algorithm in given conditions. The edge preserving property of the algorithm is also a key feature of the algorithm (see Figures 8 and 9).

Comparison with Classical Algorithms

In this section, we decided to compare the performance of our algorithm with the performance of classical algorithms that were parallelized. We choose to use the Gaussian filter (of size 7×7) and the Median filter (of size 7×7). The performances can be observed in Figures 10 and 11.

To qualitatively represent the result of this study, we made available four videos at the address related to the following reference (Ouarti (2012). These videos are the compressed versions of the videos. *Original_compressed.avi* represents the

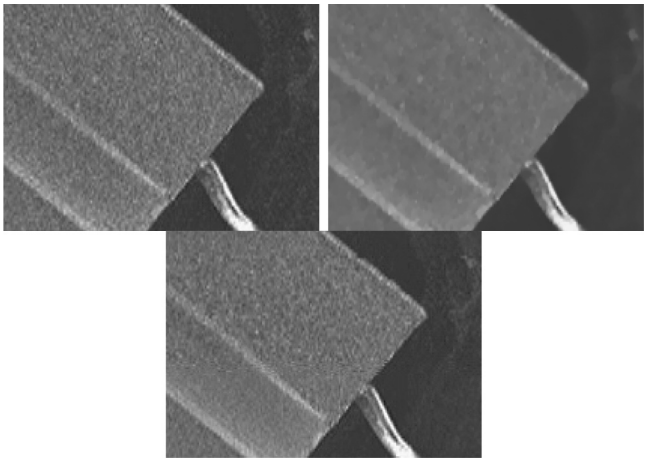

Figure 8. Details of Noisy image real-time regularized with our technique, Mode 4 condition. (*a*) noisy image. (*b*) denoised image. (*c*) reference image. The edge preserving property of the algorithm can be observed. The fluctuations were removed.

original video compressed at 25 Hz, *Gauss_filter_algo.avi* represents the results in term of psnr and fps during processing recorded at 25 Hz, *Median_filter_algo.avi* for the median filter algorithm, and *TV_algo.avi* for the total variation algorithm.

The PSNR and the fps are displayed. The reference image for the PSNR is the first frame. It can be also observed that the fps increase in the first seconds of the video. This behavior is due to the increased load on the GPU.

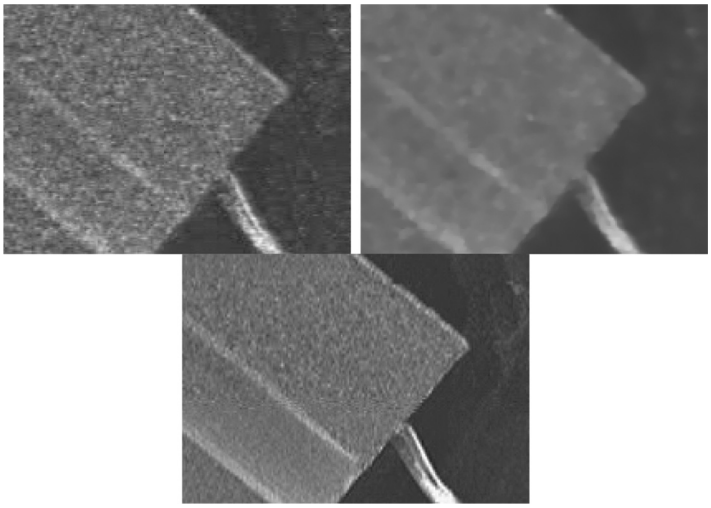

Figure 9. Details of Noisy image real-time regularized with our technique, TVSCAN condition. (*a*) noisy image. (*b*) denoised image. (*c*) reference image. The edge preserving property of the algorithm can be observed. The fluctuations were removed.

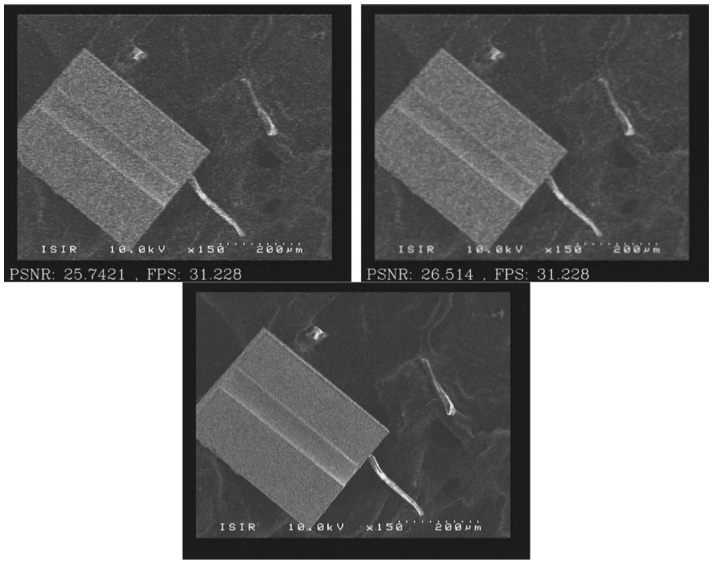

Figure 10. Noisy image real-time regularized with the Gaussian filter (TVSCAN condition). (*a*) noisy image (PSNR = 25.74). (*b*) denoised image (PSNR = 26.51). (*c*) reference image for the computation of the PSNR. Fps = 31.23.

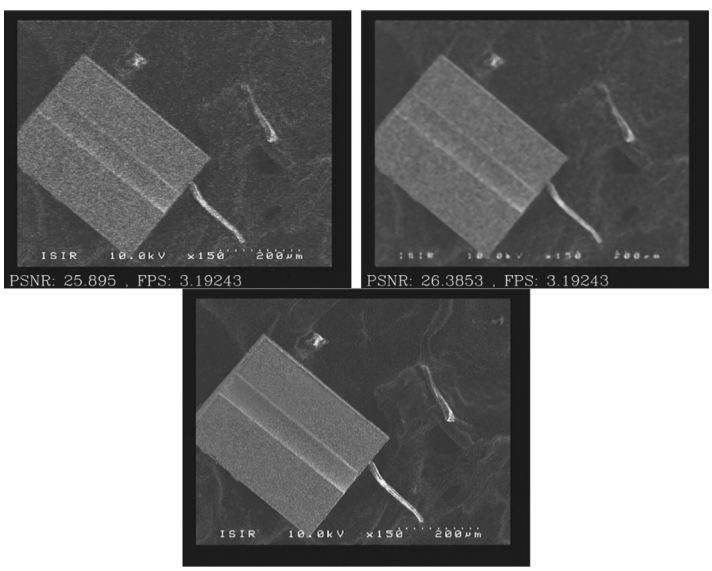

Figure 11. Noisy image real-time regularized with the Median filter (TVSCAN condition). Top Left: noisy image (PSNR = 25.90). Top Right: denoised image (PSNR = 26.39). Bottom: reference image for the computation of the PSNR. Fps = 3.19.

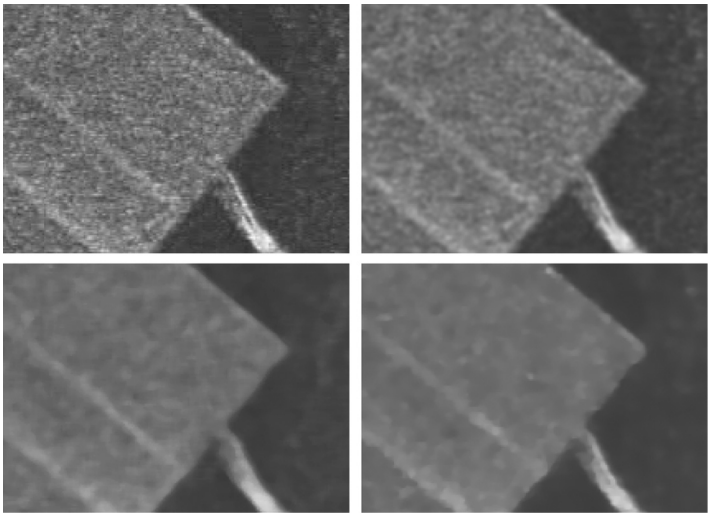

Figure 12. Details of Noisy image real-time regularized with the Gaussian filter, Median filter, and Total Variation, in the TVSCAN condition. (*a*) noisy image. (*b*) denoised image with the Gaussian filter. (*c*) denoised image with the Median filter. (*d*) denoised image with Total Variation. The blur effect of the algorithm can be observed for the Gaussian filter. The Median filter and Total Variation look similar but the edge preservation is sharper for Total Variation.

DISCUSSION

Aim of the Experiment

The aim of this study is to obtain the best image quality in the minimum amount of time. The PSNR represent an assessment of the quality of the image, i.e., the difference between the image to be assessed and the original image. Secondly, the fps represented in our framework is related to the period of time needed to compute the data with the different algorithms. Fps is the inverse of the period of time to process one frame. For this reason, we sought to obtain the highest psnr for the highest fps.

Total Variation on GPU

We proposed a new method which quantifies the fluctuation (noise) which is present in a SEM image. This noise is principally characteristic of the SEM, mainly dependent of the rasterizing time. Given an estimated noise we applied a gradient method, GPU Total variation, that removes this noise for pictures taken in real-time. This allowed creating real-time videos with a good definition and sharp edges. With this technique an SEM can be used not only like a tool that take pictures at micro-nanoscales, but rather like a real-time video device that films at micro-nanoscales. This result can be reached with no modification of the SEM's hardware and can be adapted to potentially every SEM.

In this study, we showed that we can estimate the optimal parameter λ^* but also that we can take advantage of the relation between this parameter and the number of iterations to converge in the case of Total Variation.

We also showed that the number of iteration can be drastically decreased with a reasonable loss of quality. We then showed that it is possible to obtain a real-time version of the algorithm using these properties and the GPU computation.

In this study we found a good tradeoff between the quality of image and the processing time. The first advantage of the Total Variation technique is its edge preservation property. It means that the most important information concerning the shape of the object is preserved. For instance, it can be important for the real-time determination of the 3-D shape of a given object.

However, with this technique the fine details like textures are mainly removed from the image, it is one of the limitations. It can be observed on the detail image of the Figure 8 that the texture of the object is removed, considered as noise. But, in the majority of the applications (assembly, micromanipulation), the texture of the objects is not required and it is more important to be able to observe the tridimensional shape of the objects. This drawback does not seem to cause problems in the vast majority of the applications. Based on the real-time properties of the imaging algorithm, the perspectives are the possibilities to manipulate and to observe an object in parallel (Xie et al. 2009). The nano-manipulation is usually very costly and this method could provide an accessible alternative.

Estimation of λ

Calculating the best lagrangian multiplier is equivalent to estimating the noise in an image. The advantage of SEM is the possibility to access the denoised version of the image and then to quantify the noise based on the original image. In many applications, this is not possible and the noise is estimated"on-the-fly." Without reference, there is no guaranty that the estimation of the noise is the best one. Here, it was possible to prove the accuracy of our algorithm using original data. The other problem is to have an accurate model of noise because the majority of algorithms that compute the noise are based on a model of the distribution of this noise (Liu et al. 2006; Zlokolica et al. 2006). Without an *a priori* on this distribution, we decided, in our case, to use an algorithm to find the best lagrangian multiplier.

Relation Between λ and Fps

There is a relation between λ and the computational cost of the algorithm and then the fps. A smaller λ has the property to remove more noise in the image but computationally speaking a small λ causes an enhancement of the number of iterations needed for the Total Variation algorithm to converge. But we showed, here, that it is possible to decrease the number of iterations.

Comparison Between the Different Algorithms

Another contribution of this work was to also compute traditional denoising algorithms on GPU that can be compared with Total Variation. We considered the gaussian filter and the median filter as good candidates. The gaussian filter algorithm is very fast particularly in this case with GPU parallelization. The limitation of gaussian filter is its blur effect, the edges are not preserved. The median filter is a

better algorithm to preserve edges, but the limitation is its high computational cost, for sorting N pixels, the temporal complexity is $O(N \cdot \log N)$. This high computational cost leads to a very small fps even with our parallel implementation. The quality of the denoising for the median filter is not so different from the total variation denoising, but the computational cost is totally different. Another point of difference is that median filter has the tendency to remove very small objects like the letter in the video. This is not the case for Total Variation for a moderate denoising level.

Real-Time Computation

Indeed, our aim was to perform high-quality denoising as quickly as possible. We reach 13 fps, with a Total Variation, on a GPU which is not very powerful compared to more recent GPU. Our definition of "real-time," in this study, was the ability of our algorithm to grab a frame, to denoise it, and to display it, in the interval between two frame captures. In our case we considered, the TVSCAN condition where the fps is 12.5. In this mode we succeed in obtaining a real-time algorithm.

CONCLUSION

In this study, we were focused on the Hitachi SEM S4500. But, the same method can be applied on more modern SEMs. For every SEM, there is a tradeoff between image quality and scanning time. And our technique allows, for a given SEM, to obtain a better quality when increasing the scanning speed.

These preliminary results are encouraging and the method exposed in this study is totally general and can be applied with different denoising techniques. So the first extension could be theoretical. Another promising point is the hardware enhancement, and particularly the GPU used in this study which is not the most recent. With a more powerful GPU, a faster application could be generated.

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