Machine learning for identification and counting of Naturally Occurring Asbestos*.

Nazha Selmaoui-Folcher[1], Nathaël-Christian Galante-Gras[1], Christine Laporte-Magoni[1], Francesco Turci[2,3], Jasmine Rita Petriglieri[2,3]

[1] ISEA (Institut des Sciences Exactes et Appliquées) – University of New Caledonia
[2] "G. Scansetti" Interdepartmental Centre for Studies on Asbestos and Other Toxic Particulates, University of Torino
[3] University of Torino, Department of Chemistry
* Corresponding author: nazha.selmaoui@univ-nc.nc

Introduction

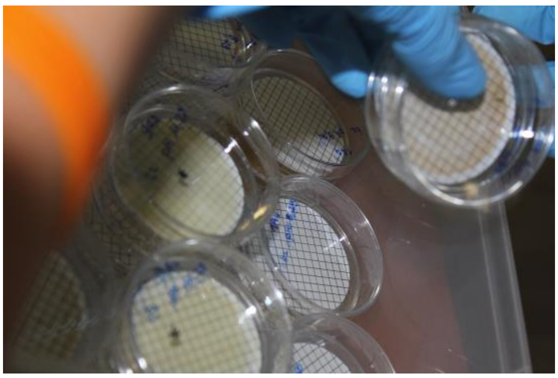
Open-pit nickel mining is the main economic activity in New Caledonia. Lateritic Ni-ore deposits formed on weathered ultrabasic rock cover more than a third of the territory. However, among the mineral phases that make up these laterites, some belong to the asbestos family and have the capacity to emit pathogenic fibres. The inhalation of air polluted by such fibres may lead to severe respiratory diseases; asbestos may penetrate deep into the lungs causing at worst malignant mesothelioma.

In order to manage the natural occurrence of these fibres and take the necessary measures for the protection of workers, it is necessary to evaluate and monitor the concentration of asbestos fibres into the environment (e.g., airborne, waterborne). The current monitoring approach adopted by asbestos laboratories relies on counting method using Transmission Electron Microscopy (TEM), according to French regulation (NF X 43-050). Analysts operatively count and measure fibres and elongated mineral particles (EMPi) with on a filter viewed through the microscope device at high magnification. It is worth noting that analytical procedures involving electron microscopies are time-consuming, and show an intrinsic bias related to the subjectivity of operator analysis. These drawbacks explain the need to develop an automatic method for fibre and EMPi detection and quantification.

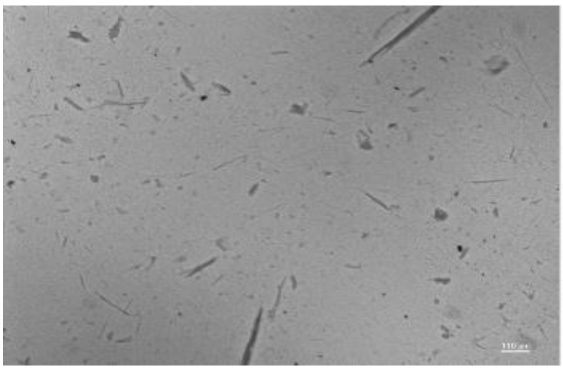
This paper presents a new method for detecting fibres on filters by using image processing and machine learning methods, discriminating single fibres, particles, juxtaposed objects and fibre bundles, minimizing as much image noise.

Methodology and results

The approach we will present was mainly tested on raw filter images similar to those obtained during air quality monitoring measurements (cf. Figure 1.a).



a



b

Figure 1 : a) Sample filter, b) Microscopic image

Images are acquired by a conventional optical microscope and correspond to about 1.6µm per pixel.
Approach developed follows the complete process presented in Figure 2.

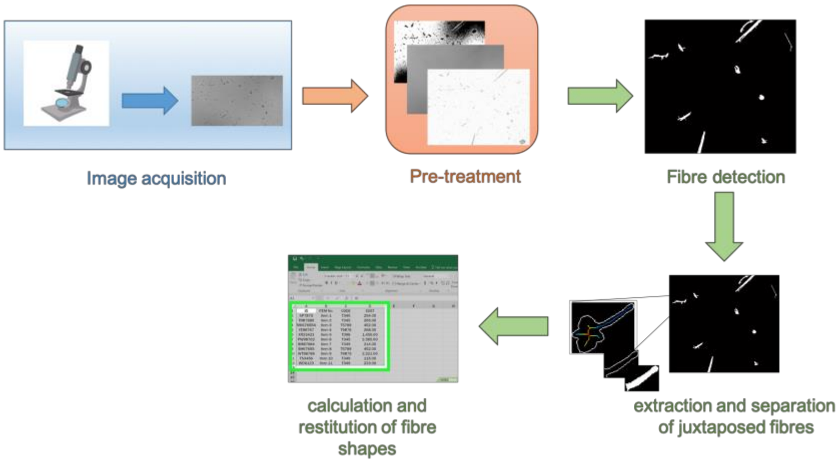
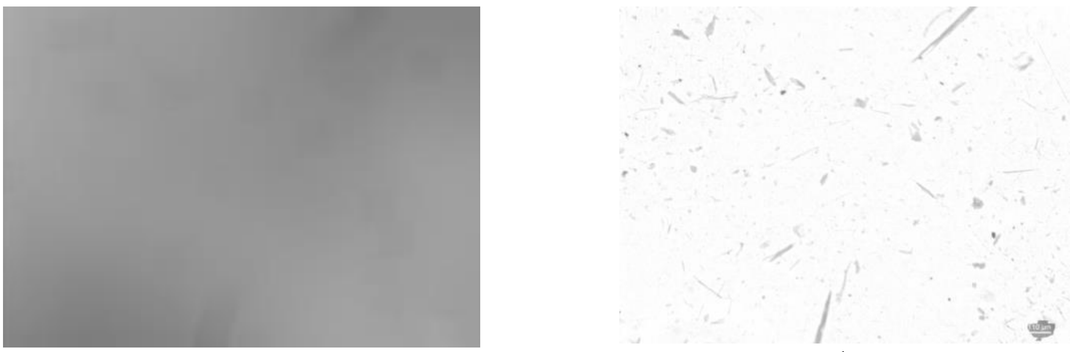


Figure 2 : Complete process from acquisition to final result

The Pre-processing Step consists of restoring the image by eliminating noise and uniforming image with lighting defects (see Figure 3). To do this, a low-pass filter has been applied to keep only low frequencies. These low frequencies correspond to spatially wide variations in intensity. This operation transforms the original image into an image which represents the background (see Figure 4.a).

Figure 3: Example of image showing a defect due to non-uniform lighting

A substraction between the original image and the background image will correspond to an almost clean image (see Figure 4.b).

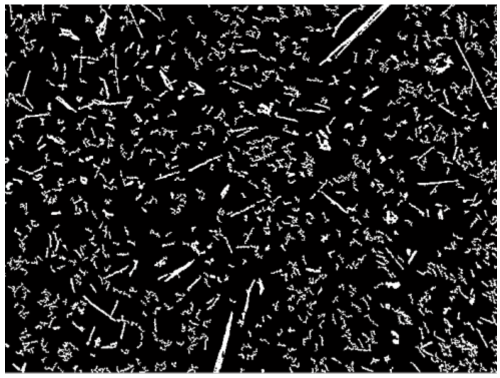


a b

Figure 4: a) background of the original image, b) Image result from background substraction

In the pattern detection step, we used the so-called LOG (Laplacien Of Gaussians) method. To avoid the suppression of small fibers during detection, we chose a 50x50 pixels mask which corresponds to the order of fibers size magnitude. Figure 5.a shows the result of the LOG filter application, after a white threshold (s=255). A post-processing, using directional morphology, allowed to eliminate some persistent noise, the final result is shown in Figure 5.b.

a



b

Figure 5 : a) filtered image by LOG, b) Thresholded image

The last step, before calculating the shape indexes of each fibre, is to separate the juxtaposed fibres. This last post-processing step consists in reconstructing and separating certain juxtaposed shapes. This method will need to be invested and improved in the future.
Finally, shape indices were calculated and made it possible to finalise the sorting of fibres by removing those shapes that do not perfectly correspond to the definitions of a fibre provided by the experts.
This last step does not eliminate all forms considered as non-fibre. An initial labelling (fibre or non-fibre) was carried out on the resulting image (binary) by the experts with the naked eye. Then, we applied a supervised classification method (machine learning) with shape indices as attributes to verify that the predictive model does indeed allow the discrimination between fibres and non-fibres. We obtain an accuracy around 95% of good classified classes. But there is a bias because the database is unbalanced, we have 1247 non-fibers versus 133 fibers. We will therefore have to complete the database in the further work.

Conclusion

We have developed a chain for processing and analyzing microscopic images of asbestos fibres for automatic and rapid recognition and counting of these fibres. The aim is to offer a complete process to experts that allows them to free themselves from any subjectivity of interpretation. Moreover, it will allow to build a base of morphologies per asbestos in order to exploit the capabilities of machine learning methods.

Machine learning for identification and counting of Naturally Occurring Asbestos

***Nazha* Selmaoui-Folcher,**

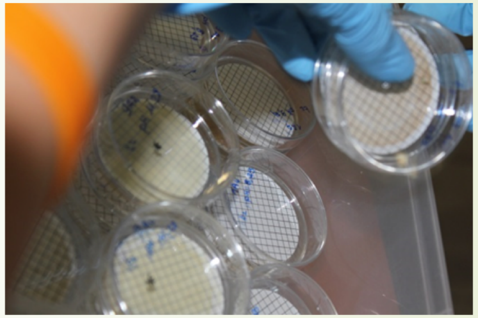
Nathaël-Christian Galante-Gras, *Christine* Laporte-Magoni, *Francesco* Turci, *Jasmine Rita* Petriglieri

Context and issue

Opencast Mines

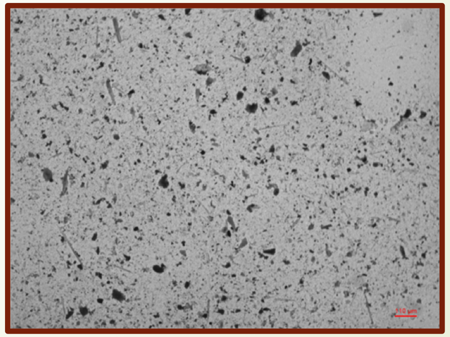
- Open-pit mining operations
- Natural outcrops of hazardous fibres

↳ ***Protection and prevention of risks for workers***



- Monitoring of fibre concentrations in environment
  - ✓ *Long process*
  - ✓ *Painful to achieve*
  - ✓ *Non-objectivity of experts*

➡ Need to develop a (semi-) automatic process for fibre detection and counting by filter image analysis



Methodology

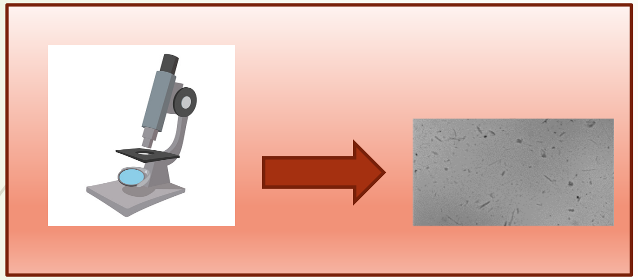
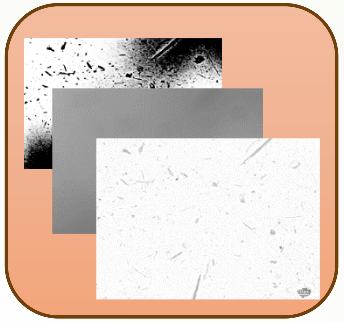
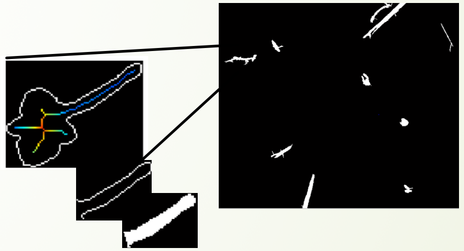


Image acquisition

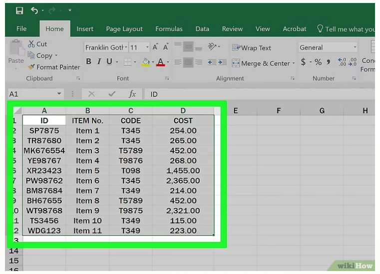


Pre-processing

Fibre detection



extraction and separation
of juxtaposed fibres



ID	ITEM No.	CODE	COST
SP7875	Item 1	T345	254.00
TR87680	Item 2	T345	265.00
MK676554	Item 3	T5789	452.00
YE98767	Item 4	T9876	268.00
XR23423	Item 5	T098	1,455.00
PW98762	Item 6	T345	2,365.00
BM87684	Item 7	T349	214.00
BH67655	Item 8	T5789	452.00
WT98768	Item 9	T9875	2,321.00
TS3456	Item 10	T349	115.00
WDG123	Item 11	T349	223.00

calculation and
restitution of
fibre shapes

Conclusion

- offering a complete process to experts
- Building a labeled database with fibre or non-fibre classes
- Construction of a predictive model with shape indices and physico-chemestry conscentration as attributes
- Developping a tool for exepert

Project that benefited CNRT funding