# A Methodological Approach for Combining Super-Resolution and Pattern-Recognition to Image Identification

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**Abstract**—Image acquisition systems integrated with laboratory automation produce multi-dimensional datasets. An effective computational approach for automatic analysis of image datasets is given by pattern recognition methods; in some cases, it can be advantageous to accomplish pattern recognition with image super-resolution procedures. In this paper, we define a method derived from pattern recognition techniques for the recognition of artefacts and noise on set of images combined with super resolution algorithms. The advantage of our approach is automatic artefacts recognition, opening the possibility to build a general framework for artefact recognition independently by the specific application where it is used.

*Keywords*: super-resolution, pattern-recognition, AFM microscope, image analysis.

## 1. INTRODUCTION

Image understanding tasks relies particularly on the recognition of the semantics of an image, thus in order to perform it in an automatic fashion, it is important to have high-resolution images. In our work, we study super resolution (SR) algorithms enabling to have a higher density of information in our data so to be able to apply pattern recognition (PR) algorithms on these resulting images, with the final goal of recognizing features of the analysed images [1, 11, 13].

Applying image analysis to screening devices, this paper will focus on the direct correlation between SR and PR methods. In particular, PR algorithms will be used to recognize patterns on images recorded from devices and to provide an accurate feedback using machine learning algorithms (e.g., for checking real time device operability).

SR algorithms generate a denoised-hyperesoluted image (or a set of images) from low resolution ones. The knowledge of the class of images to analyse helps during the computation of the high-resolution image. The higher information contained in the generated image provides a better sample that can be profitably used by PR algorithms. The results provided from the PR algorithm supply an input for the machine learning algorithms that gives the possibility to change the device regulation in order to obtain better images.

This operative procedure can be applied to a big set of devices used for automated data acquisition. In fact, in environments with a high grade of automation there is usually a huge production of image datasets, which can be hardly hand checked so it is necessary provide an automated control system producing an intelligent feedback to the devices in order to improve the efficiency. With the purpose to demonstrate the generality of our approach, we will apply our algorithms to images obtained using Scanning Probe Microscopy (SPM) technique. Such technique, commonly operating at molecular scale, records data and represents them in an image, i.e., a matrix $(x; y; z(x, y))$. In addition, the advent of SPM family devices since the 1980's opened the possibility to observe and manipulate matter at atomic scale making possible to improve the knowledge and technology on nanoscale (commonly claimed Nanotechnology). Nevertheless, today the application of SPM techniques is limited by the fact that the experimental scanning best conditions can be found only manually.

After a theoretical analysis of the pipeline processing composed by SR and PR algorithms, and device control by means of artificial intelligence algorithms, we will focus our efforts in a possible application on a SPM device.

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## 2. AN OVERVIEW ON SUPER-RESOLUTION METHODS

The introduction of digital images, for example by the means of surveillance camera, led to the analysis of single-frame or multi-frame images. These two kinds of image collections involve different methodologies of analysis, e.g., even if in a video each frame represents different images, sequential frames are quite close one each other, so that it is possible to use them in order to process the whole sequence.

SR algorithms transform low-resolution images into higher resolution images. In order to produce the high-resolution image it is necessary to remove the effects of possible blurring and noise from low resolution images. The focus of SR algorithms is on the identification and reduction of blurring, noise and aliasing from low resolution images [1–3, 6, 7].

SR algorithms are applied to a large number of problems such as satellite imaging, astronomical imaging, video enhancement [8, 9] and restoration, microscopy [10] and other.

During the process of resolution enhancement, SR algorithms create an empty grid and fill it with pixels belonging to the high-resolution image. The filling process determines the SR method used.

The resolution of an image is determined by many factors depending on the acquisition system, Eq. (1) describes the imaging model used (based on [28]):

$$L(x, y) = S(x', y') * H(x' - x, y' - y) + N(x, y), \quad (1)$$

where $S(x', y')$ is the point spread function (PSF), $H(x' - x, y' - y)$ is the ideal image, $L(x, y)$ is the original image and $N(x, y)$ is the noise. This brief introduction explains the main super-resolution methods working both on single-frame and multi-frame datasets. Another important aspect regards the analysis domain of the SR methods: it can be performed either in space domain or in frequency domain.

Using the single-frame SR methods the algorithm get a single image as input and all the low-resolution image pixels are placed in the high-resolution image grid. The algorithm leaves some unfilled pixels in the high-resolution image grid during the filling process. Those pixels are filled according to a function that defines the filling method.

The single-frame (or single image) SR methods can super-resolve an image by:

—performing a pixel interpolation;

—performing inference, e.g., using a neural network.

The main SR single-frame interpolation methods are bilinear interpolation, nearest neighbour interpolation and bicubic interpolation.

Bilinear interpolation is an efficient and simply way to enlarge images. During the bilinear interpolation, the image is analysed to find a bilinear surface that fits across the existing pixels. The result is a high-resolution image with smoothed borders. This method fills any empty pixel with a value affected by the nearest four existing pixels depending on the reciprocal distance.

In Fig. 1 top is shown a basic result using bilinear interpolation.

An advanced version of the bilinear interpolation is the Bicubic interpolation [15]. Bicubic interpolation uses a 4 × 4 neighbourhood to find the missing pixels in the high-resolution grid. The value of the calculated pixel is based on the computation of a polynomial that uses as coefficient the value of the neighbouring pixels in the low-resolution image. This method uses a convolution-based interpolation that works on uniformly sampled data. The use of this method requires the solution of a linear system [15].

Figure 1 (bottom) shows an example of application of bicubic interpolation.

A common feature inherent the described super-resolution algorithms is that they can be characterized as nearest neighbour (NN)-based estimations. This characteristic gives several advantages in terms of computational time and a simplification on conceptual assumptions on Eq. (1). For example, another approach to single-frame super-resolution has been introduced recently in [16, 17]. Figure 2 shows a super-resolved image using the algorithm described in [16].

Their algorithm evaluates the high-frequency of the desired high-resolution image. The estimation of high-frequency components is performed using the Laplacian of the bicubic interpolation of the image. The high-frequency components are then added to the bicubic to produce the super-resolved image. Let us define $Y$ the high-frequency components and $X$ the bicubic interpolation ($H$ the super-resolved image). $H$ is calculated adding $X$ and $Y$. To retain the complexity of the resulting regression problem at a moderate level, a patch-based approach is taken where the estimation of the values located in a patch$N_N(Y(x, y))$ is performed based only on the values of $X$ at the same corresponding patch $N_M(X(x, y))$, where $N_G(S(x, y))$ represents a $G$-sized square window (patch) centered at the location $(x, y)$ of the image $S$.

During the super-resolution computation, $X$ is scanned with a small window (of size $M$) to produce a patch-valued regression result (of size $N$) for each pixel. This, results in a set of candidate pixels for each location of $H$ (as the patches are overlapping with their neighbours), which are then combined to make the final estimation.

For each point $(x, y)$ a set of $N$ estimator is calculated so that for each point it is produced an estimation set of differences $(\{d_1(x, y), \ldots, d_N(x, y)\})$ between the unknown desired output and each candidate. The final estimation of the value of the pixel in an image location $(x, y)$ is obtained as the convex combination of candidates given in the following form:

$$H(x, y) = \sum_{i = 1, \ldots, N} \omega_i(x, y) L(x, y), \quad (2)$$

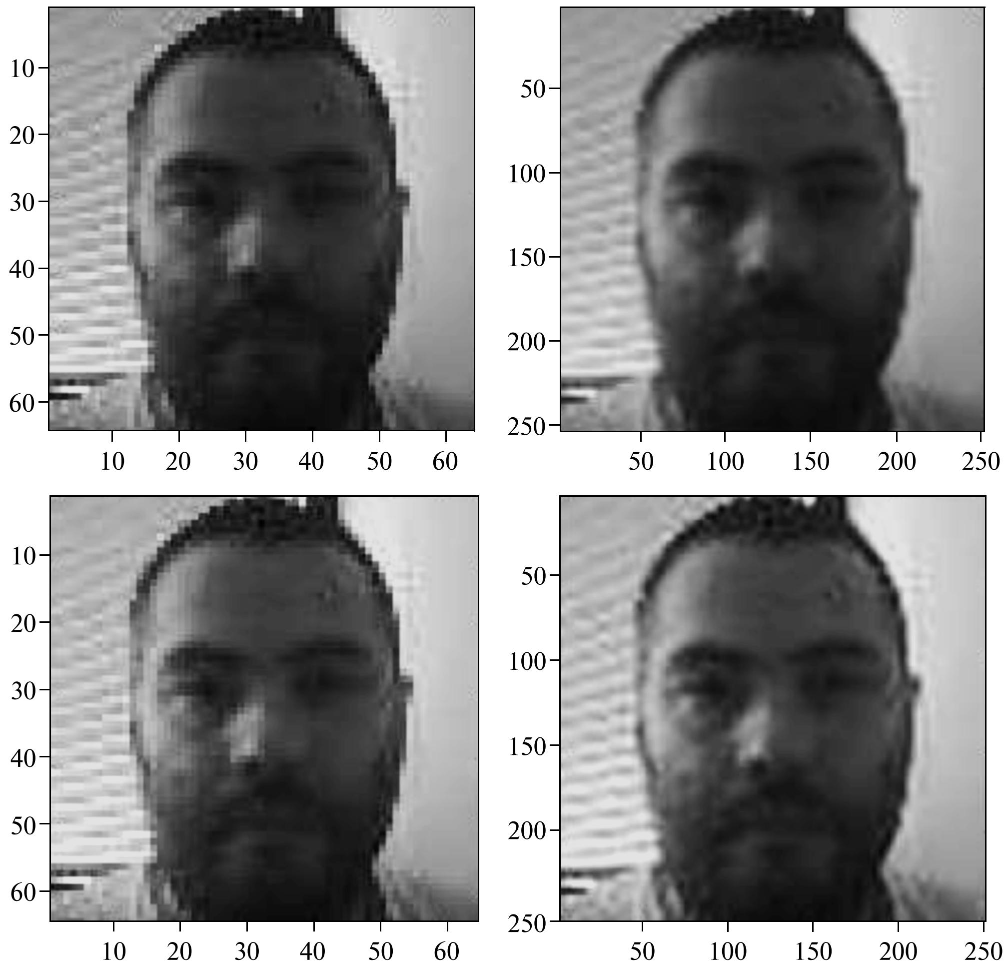


**Fig. 1.** An example of bilinear interpolation (top: on the left the source image, on the right the 400% zoomed image using bilinear interpolation) and bicubic interpolation (bottom: on the left the source image, on the right the 400% zoomed image using bilinear interpolation).

where

$$\omega_i(x, y) = \left[e^{\frac{d_i(x, y)}{\sigma_C}}\right] \Big/ \left[\sum_{i = 1, \dots, N} e^{\frac{d_j(x, y)}{\sigma_C}}\right]. \qquad (3)$$

In particular, each $d_i(x, y)$ is the estimation of distances between the unknown desired output and each candidate. This estimate is calculated using a set of linear regressors,

$$d_i(x, y) = \left|PH(x, y)^T W_i\right| \quad i = 1, \dots, N, \qquad (4)$$

where $PH(x, y)$ is a vector constructed using the concatenation of all columns of a spatial patch of $H$ centred at $(x, y)$ and the parameters $W_i$ are optimized based on the patch-based regression results $H$ for a subset of training images. $\sigma_C$ is a constant (typically 0.006 for a magnitude factor 4).

Zou et al. [14] have described a recent approach to the SR, dedicated to face recognition. To overcome the very low-resolution problem (using faces with 16 × 16 pixels) they perform SR as a regression problem with two new constraints on the given training data. The method firstly determines the mapping pattern (relationship $R$) between very low-resolution and high-resolution face image spaces, in order to do this they use the information from the training data, and then recover the high-resolution images by applying the relationship operator $R$ on low-resolution images. Figure 3 shows an application of the Zou's algorithm [14] used during the algorithm test.

Through a regression model, minimizing the proposed constraints, the relationship $R$ is learnt. The meaning of these constraints is to minimize the error between the high-resolution image and the calculated high-resolution image.

## 3. PATTERN-RECOGNITION METHODS AND FEATURES EXTRACTION

Observing an image a human can notice some particular patterns or characteristics that are unique for a certain type of material. This inference process is use-

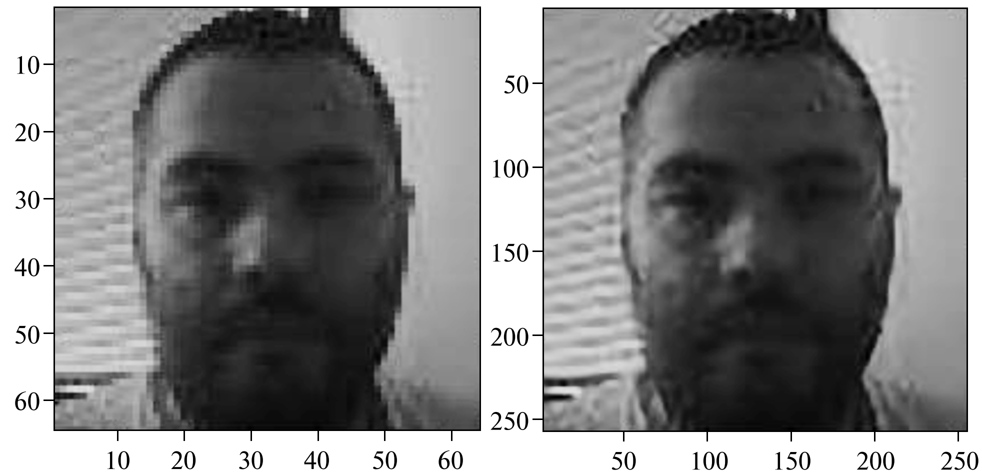


**Fig. 2.** An application of the single frame super-resolution algorithm described in [16].

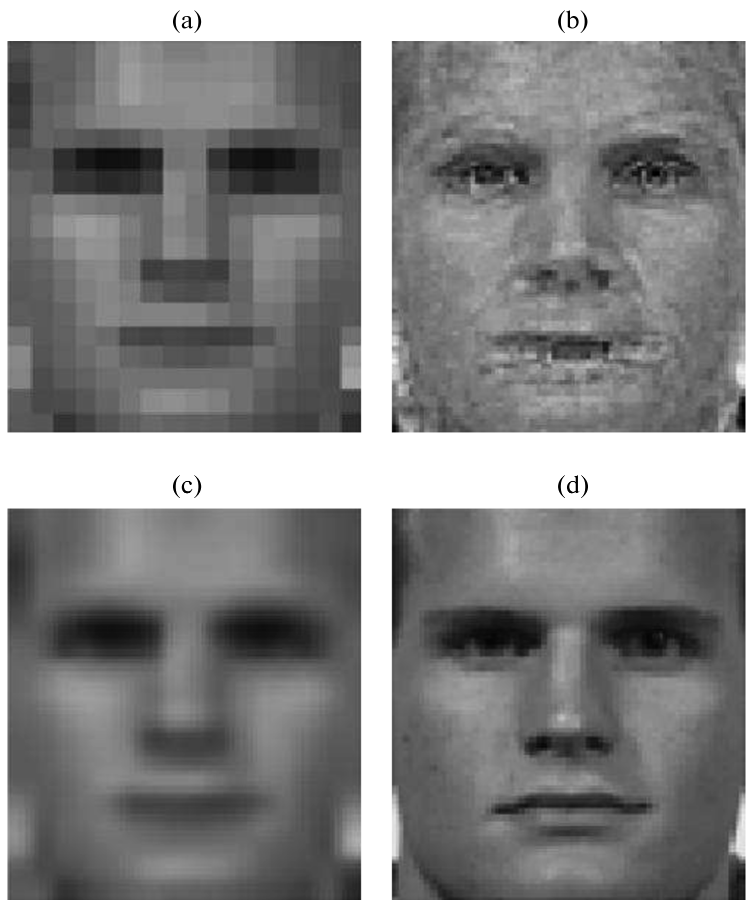


**Fig. 3.** A face is used during the algorithm test. (a) It shows the source image, (b) is the output of Zou algorithm that we can compare with (c) that is obtained with a bi-cubic interpolation, finally, (d) is the original high-resolution images.

ful in order to observe various types of phenomena, for example, in computer vision a computer can analyse a set of matrices for each image in which the colours are coded using a particular colour code. The data extraction performed by a computer and its interpretation is a task that permits to a machine to recognize patterns and regularity and to provide an interpretation.

The main approaches to pattern recognition can be classified among either statistical learning or classification.

Statistical learning is extremely important as shown in numerous examples, such as for the prediction of the price of a stock in advance [11], estimation regarding e-mails categorization (e.g., whether it is or not spam), recognition of handwritten characters and digits, and understanding of whether an image contains or not archaeological handmade objects [12]. Learning problems can be divided into two sets: supervised and unsupervised learning. In supervised learning an algorithm provides a predictable output based on a set of input measures and a feedback from a supervisor (i.e., a user or an expert), in unsupervised learning the algorithm objective is to autonomously "understand" the relation between a set of input (i.e., analysing and identifying recurrent patterns).

On the other hand classification based approaches are based on predictors $P(x)$ which takes values in a discrete set $S$. Usually the outcome of the classification is a division of the input space into labelled regions. The boundaries between the regions can be rough or smooth. For each input data $x_i$, the classifier provides a $g_i$ as output, where $g_i \in S$. Various methods exist to determine $g_i$: prototype, $K$-means clustering, learning vector quantization, $K$-nearest neighbours, neural networks, kernel methods and support vector machines [13].

When the acquired data has large dimension, it needs to be computed using either automatic or unsupervised methods. This task can be performed using methods of PR. In particular, PR resolves the problem of feature extraction so that we can create a relationship between significant features as shown in [18].

We can formalize the meaning of feature extraction as a function $Y = f(X)$, where $X = [x_1, ..., x_n]^T$ is the vector that characterizes the studied phenomenon and $Y = [y_1, ..., y_n]^T$ is the vector of the mapped features [19, 20].

The function $f$ characterizes the algorithm of feature extraction and selection. It can be selected according to the task to resolve. It can be either linear or non-linear function, but usually real problems require the use of a non-linear function.

The use of statistical analysis theory is a classical approach to the problem of feature extraction and selection. Main methods are: Principal Component Analysis (PCA) [29], Linear Discriminant Analysis (LDA) [22], Factor Analysis (FA) [22], and Ordinary Least Square (OLS) [23]. Other relevant methods for features extraction are: entropy pattern recognition methods, based on Shannon work [4], and methods based on Artificial Neural Networks (ANN) [5, 21]. Usually an ANN is a mathematical model defining a function $f$: $X \longrightarrow Y$ or a distribution over $X$ or both $X$ and $Y$, but sometimes the model is also closely associated with a particular learning algorithm or learning rule.

## 4. A COMPUTATIONAL APPROACH FOR COMBINING SUPER-RESOLUTION WITH PATTERN-RECOGNITION

In this section the implemented algorithm, combining SR and PR methods is described. It runs on single frame basis method, the steps are as follows: 1—it takes an input image, 2—it firstly super-resolves the image with an interpolating algorithm, then 3—extracts some features in order to apply PR methods, and 4—generates a super-resolved image guided by the discovered model. Figure 4 shows the main steps of our algorithm.

While, at the end of this section, we report a *high-level* pseudo-code, following the steps of the algorithm. The first step consists of reading an image and generating a super-resolved one. In particular, among all the methods previously mentioned, the ones tested have been: bilinear interpolation, bicubic interpolation, Kim-Kwon algorithm [16] and Zou algorithm [14]. The best results were obtained using Kim-Kwon algorithm (line of pseudo-code 02 in the pseudo-code at the end of this section).

In order of apply a PR method, it is necessary to extract some features and recognize the kind of image under investigation. The feature extraction process involves the lines of pseudo-code 03-07. On line 03 the image is segmented using Otsu's method [24, 25].

Using a PR technique in accordance with [11], the algorithm extracts 8-connected components from the SR segmented image using Matlab function *bwconncomp* (line of pseudo-code 05) [26]. Considering that the image we want to recognize in our case study is a grating fully composed of parallel structures, the algorithm extracts the orientation property from the 8–connected components. This was done using the *regionprops* Matlab function (line 06) [27].

The orientation is a scalar value representing the angle (in degrees ranging from –90° to 90°) between the $x$-axis and the major axis of the ellipse that has the same second-momentum as the region. Figure 5 displays the axes and the orientation of the ellipse. The left side of the figure shows an image region and its corresponding ellipse. The right side shown the same ellipse, with features indicated graphically: the solid cross represents the axes, the two dots are the foci, and the orientation is the angle between the horizontal dotted line and the major axis.

After this calculus, we consider the connected components that are parallel (after the elimination of the outliers, line 07); we use the grating model in order to super-resolve the recognized input image (line 08). At this stage, if the pattern cannot be identified as a grating, then, the algorithm returns the HR calculated with the Kim-Kwon's algorithm [14] (in line 02).

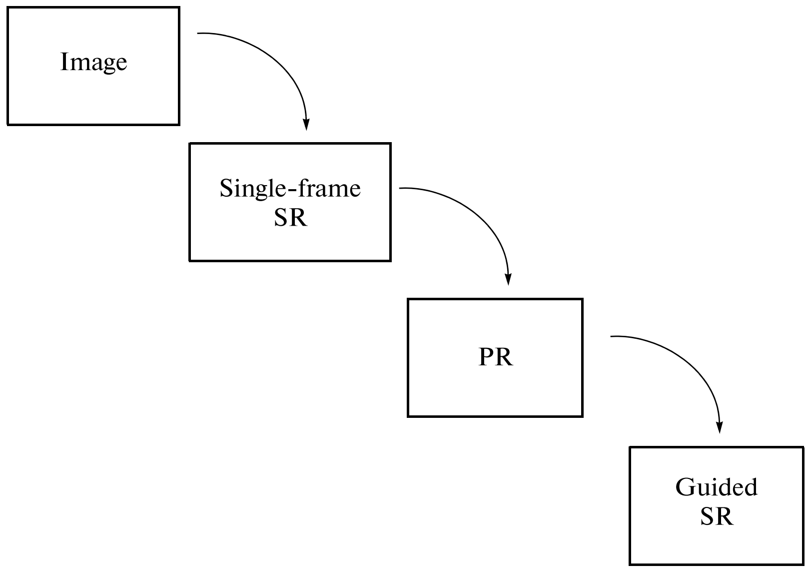


**Fig. 4.** The implemented algorithm data-flow.

The pseudo-code of the algorithm is the following:

```
VHR-IMAGE SR(L) {
HR=KK_HR(image);
Threshold=otsu(HR)
 HR_segmented=
      segment(HR,thereshold);
 connected_components=
      8_connection(HR_segmented)
 orientatation=
  comp_orient(connected_components)
if (outliers<standard_deviation)
    VHR=super_resolute_grating(HR);
Else
      VHR=HR;
Endif }
```

## 5. A CASE STUDY: AFM IMAGING IMPROVED BY PR METHODS COMBINED WITH SR

Among the SPM family, Atomic Force Microscopy (AFM) mechanism is based on the sensing of the force between a surface of a specimen and a sharp probe. A cantilever oscillates and touches the sample, continuously, or only intermittently, scanning the object and reconstructing the sample morphology line-by-line. In this way, AFM produces high-resolution topographic and force measurements in aqueous and physiologically relevant environments without the need to stain or pre-treat the specimens.

**Fig. 5.** An example of oriented region.

The most important advantage of applying AFM in biological research relates to the fact that AFM is essentially a single-molecular technique, providing insight into the geometry, elasticity, and dynamic behaviour at the level of single molecule or single cell. As many biological processes, such as protein amyloid self-assembly, involve multiple pathways and are characterized by inherent heterogeneity of species, the application of single molecule studies is of critical significance. Preliminary results applying the algorithm described in the preview section follows and are shown in Fig. 6. During our first experiments, the input of the algorithm was the acquired image reported in Fig. 6 (image B shows the 3D aspect of the surface). As a result, we have a well-characterized profile of the surface as showed in image C (picture D shows the 3D aspect of the surface).

The great advantage of AFM is that the screening procedure over large number of potential patterns can be carried out in their natural environments without their pre-treatment or fixation. This non-invasive procedure can be applied for the identification of the promising lead compounds among the large library of biological active species, which would display the largest attractive forces towards their target molecules.

Our approach for improving single image PR on biological samples is based on the following steps; first a standard PR method is applied to an image in order to define its features. The second step regards the

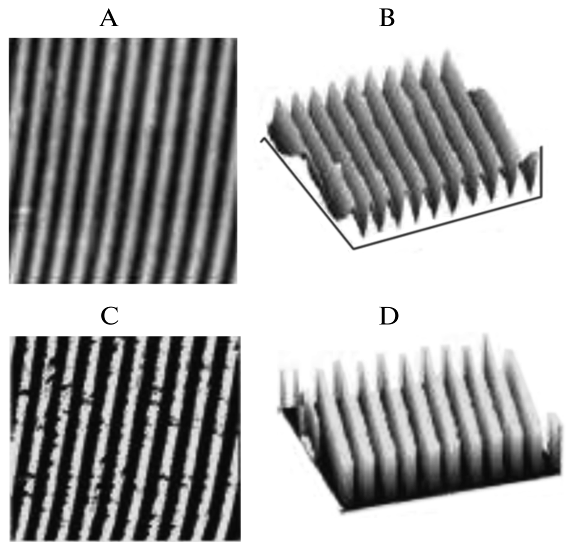


**Fig. 6.** From A to B: the input image and its 3D rendering. From C to D: the output after our data processing and its 3D rendering.

increase in pixel density of the image using SR approach and finally, the third step is devoted to pattern matching between the first image and the enhanced image.

An example of the application of our approach to biological sample is shown in Fig. 7. The image of a fibroblast cell is processed following the previously described algorithm. The pattern to be recognized are inherent the specific intra-cell organs, including subsurface actins and filaments.

Figure 7 summarizes the effective advantage of using our algorithms. From the initial image, it is possible to have an idea of the various cytoskeleton cell organs, but the low quality makes difficult to estimate the plot of such organs and their real dimensions. On the contrary, improving the pixel density in a reasonable way using SR methods makes it possible to estimate the cytoskeleton plot and to identify the components as actins and filaments with their real dimension, approximately 100 nm.

## 6. CONCLUSIVE REMARKS AND FUTURE PERSPECTIVES

In this paper, we focused the attention on an effective computational approach to increase the image resolution for improving pattern recognition. The results obtained are intended to be a first step of a more general framework for applying machine learning and artificial intelligence to various applicative fields, in a special way to nano-scale imaging, where an intelligent process finds relevant patterns without relying on prior training examples, usually by using a set of predefined rules. In details, we applied a method derived by usual pattern recognition techniques for supporting the identification of artefacts and noise on images recorded with an Atomic Force Microscopy. An immediate advantage of such automatic artefacts recognition could be the implementation of machine learning languages for AFM investigations.

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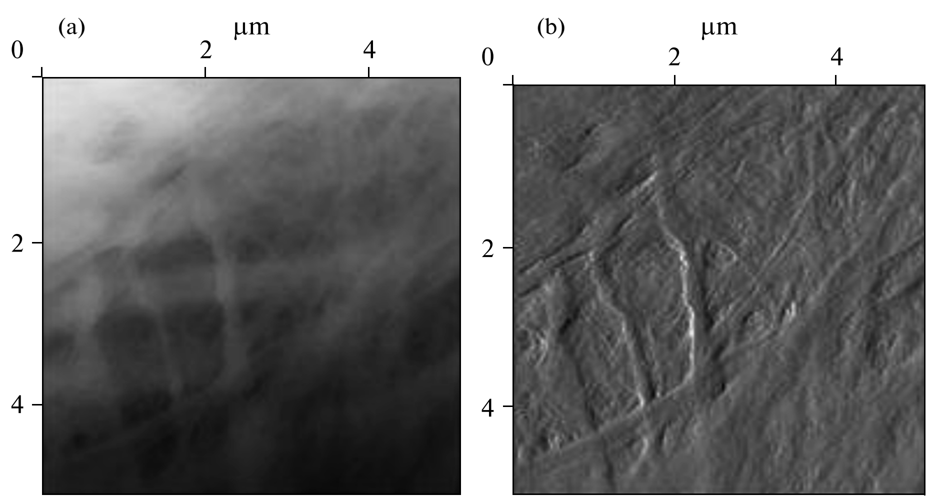


**Fig. 7.** On (a) we have a low-resolution image 5 × 5 μm of a fibroblast cell as recorder by an AFM and processed with commercial software (Park Scientific Instruments) and free available software (Gwyddion). (b) The correspondent SR image obtained using the proposed algorithm.

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