

## IMPROVING IMAGE RESOLUTION BY ADAPTIVE BACK-PROJECTION CORRECTION TECHNIQUES

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**Abstract**— The paper describes a back-projection based algorithm, improved by adaptive techniques, able to reconstruct a high-resolution image from multiple low-resolution frames. The proposed approach is mainly based on a specific metric, the uncertainty degree, used in pixel reconstruction and on a local Auto-iterative approach for error correction. Using uncertainty the amount of computation is sensibly reduced. The Auto-iterative technique reduces drastically the number of iterations needed to decrease approximation errors. This method is suitable to be applied when real-time processing is required. Experimental results are presented both in terms of perceived and measured quality.

**Index Terms**— Resolution Enhancement, Back-projection, Super-resolution, Uncertainty, Auto-iterative, Motion Estimation.

### I. INTRODUCTION

In the global communication era the need of multi-media contact is diffusing. Image capturing devices market is focused on quality improvement and reduction of the processing time [3]. Quality improvement is obtained by increasing the resolution of the sensor and/or by using more sophisticated image-processing algorithms [1], [2] and [5], while new features drive competition among the different manufacturers (video clip acquisition, MP3 player, scanning of film negative, etc).

But for specific application (e.g. mobile imaging) there are too many constraints to manage in terms of power consumption, DSP capabilities, etc. Best quality image acquisition with low cost is thus necessary. The main objective is to obtain from a low cost image sensor a High-Resolution (HR) image in a relatively short time. Zooming algorithms usually interpolate “new artificial” intra-pixel information to expand the images resolution. Simple interpolation is not well suited to generate resolution-enhanced images. Resolution enhancement techniques aim to insert “real” intra-pixel information to obtain the true matching scene.

Most mathematical theories to solve this ill-posed problem

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are presented in [6]. Almost all of them merge non-redundant image information combining multiple Low-Resolution (LR) frames. One of the LR input images is fixed as reference image. Using the data remaining from the other LR images it is possible to obtain a more accurate HR image. The methods developed so far can be divided into three main categories:

- Frequency domain methods use relationships between continuous and discrete Fourier transforms of LR frames [22];
- Bayesian approaches apply a prior stochastic model using MAP (Maximum A Posteriori) estimation techniques (e.g. integration of multiple satellite images [7], non linear expansion method [19]);
- Reconstruction methods use an iterative process on LR images starting from a “draft” HR image obtained by heuristic considerations; simple iterative projection such as Iterated Back-Projection (IBP) procedures [11], [12], update the estimated HR reconstruction by back-projecting the errors between simulated and observed LR images. IBP enforces that HR reconstruction matches the observed scene. Reconstruction methods can also be based on POCS [9], [16], [17] and [20].

All previous methods use LR image alignment to exploit LR information. Global or local motion estimation can be used depending on specific application [4], [8], [13], [14] and [18]. The proposed approach, that uses a global motion estimation algorithm, is based on a few adaptive techniques able to improve classical IBP methods. The local heuristics considered (e.g. auto-iterative, uncertainty degree) are fast and allow obtaining impressive results when applied on input Low-resolution sequences acquired by digital consumer engines.

The paper is organized as follows. Next section briefly describes previous art techniques. Section 3 introduces the proposed IBP based approach presenting a few adaptive techniques able to speedup the iterative process without perceived quality loss. The main steps are: uncertainty estimation and auto-iterative correction. In section 4 experimental results show the effectiveness of the proposed techniques. A final section closes the paper tracking directions for future works.

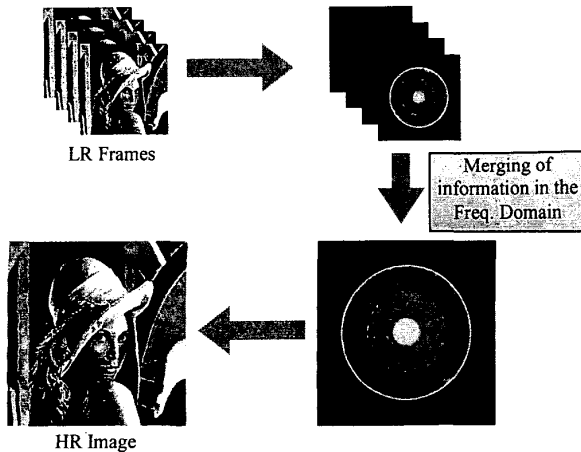


Fig. 1. Classical Frequency Domain Super-Resolution Algorithms.

## II. PREVIOUS ART

Classical “Resolution Enhancement”, or Super-Resolution algorithms try to obtain a High-resolution image from multiple Low-resolution frames. The input images must be of the same scene and must be taken at slightly different angles.

There are different mathematical approaches to solve this problem [6]. Almost all of them merge in proper way non-redundant image information combining multiple frames. Obviously, if successive frames are exact copies, no new information is available. It is important to treat properly each particular feature (e.g. object boundaries that will not be at the same pixel locations in successive frames). In this way it is possible to extract more information with respect to the original data available in a single Low-resolution image.

One of the LR input images is fixed as reference frame: the primary image (typically the first image of the sequence). The reference frame is expanded in a high-resolution grid (e.g. a 320x200 pixel Low-resolution image is expanded to a 640x400 pixel image). The complementary pixels, introduced in the expansion, could be derived using classical interpolation approaches (Bilinear, Bicubic), but in this way the real “resolution” remains unchanged. A more accurate high-resolution image is obtained using the other low-resolution frames.

Classical Super-Resolution approaches are mainly based on Frequency domain, Bayesian methods and Reconstruction methods.

### A. Frequency domain methods

One of the first Frequency domain based algorithm was presented by Tsai and Huang [22]. Such methods are based on three fundamental principles:

- The shifting property of the Fourier Transform (FT);
- The aliasing relationship between the continuous Fourier Transform (CFT) and the Discrete Fourier Transform (DFT);
- The original scene is band-limited.

Unlike all other methods, the data are initially transformed to the frequency domain where they are combined together. This data is then transformed back into spatial domain where the new image will have a higher resolution than the original frames (see Fig. 1).

The frequency domain method limits are mainly due to the simple assumption of the real image set. The existing algorithm doesn’t reach good results for the real image sequences. Moreover these methods are computationally expensive.

### B. Bayesian Methods

Bayesian methods for HR image reconstruction use a statistical *a priori* model combined with maximum *a posteriori* (MAP) or maximum likelihood (ML) formulation for HR reconstruction.

Bayes’ theorem gives the rule for updating belief in a Hypothesis  $A$  (i.e. the probability of  $A$ ) given additional evidence  $B$ , and background information (context)  $c$ :

$$p(A|B,c) = p(A|c) * p(B|A,c) / p(B|c) \quad (1)$$

The left-hand term,  $p(A|B,c)$ , is called the *posterior probability*, and it gives the probability of the *hypothesis A* after considering the effect of *evidence B* in *context c*. The  $p(A|c)$  term is just the prior probability of  $A$  given  $B$  alone, in *context c*; that is, the belief in  $A$  before the evidence  $B$  is considered. The term  $p(B|A,c)$  is called the *likelihood*, and it gives the probability of the evidence assuming the hypothesis  $A$  and background information  $c$  are true. The last term,  $1/p(B|c)$ , is independent of  $A$ , and can be regarded as a normalizing or scaling constant. The information  $c$  is a conjunction of (at least) all of the other statements relevant to determining  $p(A|c)$  and  $p(B|c)$ .

An example of Bayesian approach is given by NASA Ames Research Center [7]. NASA researchers use Bayesian theory for constructing super-resolved surface models by combining information from a set of LR images. The basic idea behind NASA approach is based on inverse graphics. That is, if it’s known what the ground is like, the lighting conditions, the camera orientation and characteristics, etc., then it is possible to predict what the camera would see (an image). This is the standard computer graphics problem. However, the problem is here inverted: it is known what the images are, and it must be found the most probable ground truth (surface) that would have generated them, assuming the lighting conditions and camera characteristics are known. The most important (and difficult) part of this process is the recovering of the camera orientation and position for each image. To do this, all the images must be registered with

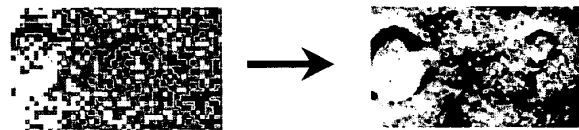


Fig. 2. An input frame (input frames are over 200) and its High Resolution result.

respect to each other by accuracy of small fraction of pixel; this registration clarifies how an image map onto the ground truth model is built. The initial ground model is formed by consenting to each pixel "to vote" on how much that ground position contributed to that pixel. This initial ground model is then used to project what each image should be (i.e. to predict each pixel value). The difference between the predicted pixel value and the observed value is used to update the ground model until it cannot be further improved. This procedure increases both spatial and gray-scale resolution.

The NASA approach was implemented with standard statistical (ML) methods. The resulting image (Fig. 2) shows a surprisingly good job of enhancing the real data more than the noise, but some graininess (quantization noise) remains. Bayesian theory offers a way to smooth out the noise without smoothing out the real features, by including neighbour correlation into the ground pixels model. In other words, in the surface reconstruction a ground pixel is not just a function of the corresponding projected pixels, but also depends on its neighbour values. This correlation addition makes NASA approach much less sensitive to noise in the pixel values, and in theory it should produce more realistic reconstruction. On the other hand this method needs many low-resolution frames to get a good output (in the order of thousands frames), and also is not suitable for consumer electronics devices.

### C. Reconstruction Methods

In this class of methods, both observation model and reconstruction are accomplished in the spatial domain. These approaches use a model relating the LR images to the desired HR image by iterative reconstruction techniques useful to estimate the HR image. The main advantage of this approach is the ability of modeling more realistic video formulation process and the flexibility of applying different iterative methods to estimate HR image. In the following we describe some of the most popular approaches.

1) *POCS (Projection Onto Convex Sets)*: Stark and Oskoui [20] have studied HR problems, using projection onto convex set (POCS). In that case the blur caused by sensor geometry is taken into account. Ozkan et alii [16] apply POCS formulation using also the sensor noise, in addition to the blur caused by the physical dimension of the sensor. These methods assume only translational motion among relative LR images ignoring the aperture time in their image model. Later Patti et alii [17] have extended the POCS based method by considering a complete model of video acquisition with an arbitrary input sampling lattice and a nonzero aperture time.

The POCS method requires the definition of closed convex constraint sets within a well-defined vector space that contains the actual HR image. An estimate of the HR image is then defined as a point in the intersection of these constraint sets, and is determined by successively projecting an arbitrary initial estimate onto the constraint sets.

A projection operator  $P$  is associated with each constraint set, mapping an arbitrary point within the space to the closest point within the set. Relaxed projection operators,

$$T = (1 - \lambda)I + \lambda P \quad \text{where } 0 < \lambda < 2, \quad (2)$$

can be also defined and used in finding an estimate in the intersection set.

The *Convex Sets* are defined in the following way: For each pixel within the LR image sequence  $g(m_1, m_2, k)$ , where  $k$  is the frame number, it is fixed, at a time  $t_i$ :

$$C_r(m_1, m_2, k) = \{y(n_1, n_2, t_i) : |r^{(y)}(m_1, m_2, k)| \leq \delta_0(m_1, m_2, k)\} \quad (3)$$

where

$$r^{(y)}(m_1, m_2, k) = g(m_1, m_2, k) - \sum_{(n_1, n_2)} y(n_1, n_2, t_i) \cdot h_r(n_1, n_2, m_1, m_2, k) \quad (4)$$

is the residual associated with an arbitrary member  $y$  of the constraint set. These sets are referred to as the *data consistency constraint sets*. Sets  $C_r(m_1, m_2, k)$  can be defined only where the motion information is accurate. Therefore it is simple to incorporate occlusion and uncovered background knowledge by only defining sets for appropriate observations. The quantity  $\delta_0(m_1, m_2, k)$  is a bound reflecting the statistical confidence, with which the actual image is a member of the set  $C_r(m_1, m_2, k)$ .

If  $y$  denotes the actual image,

$$r^{(y)}(m_1, m_2, k) = v(m_1, m_2, k), \quad (5)$$

where  $v$  is the noise due to the LR sensor. Hence the bound  $\delta_0(m_1, m_2, k)$  is determined from the possible space and time-varying statistics of the noise process and thus POCS solution will be able to model space and time-varying white noise processes.

Once *Convex Sets* are defined, for an arbitrary high resolution image  $y(n_1, n_2, t_i)$ , the *Projection operator* is constructed as follow:

$$P_r(m_1, m_2, k)[y(n_1, n_2, t_i)] \quad (6)$$

to project  $y(n_1, n_2, t_i)$  onto convex set  $C_r(m_1, m_2, k)$ , where

$$P_r(m_1, m_2, k)[y(n_1, n_2, t_i)] = y(n_1, n_2, t_i) + \begin{cases} \frac{(r^{(y)}(\cdot) - \partial_0(\cdot))h_r(n_1, n_2, \cdot)}{\sum_{o_1} \sum_{o_2} h_r^2(o_1, o_2, \cdot)}, & r^{(y)}(\cdot) > \partial_0(\cdot) \\ \frac{(r^{(y)}(\cdot) + \partial_0(\cdot))h_r(n_1, n_2, \cdot)}{\sum_{o_1} \sum_{o_2} h_r^2(o_1, o_2, \cdot)}, & r^{(y)}(\cdot) < -\partial_0(\cdot) \\ 0, & \text{else} \end{cases} \quad (7)$$

where "." function argument is interpreted as " $m_1, m_2, k$ ",  $o_1$  and  $o_2$  denote the  $h_r$  blur function support in  $y(n_1, n_2, t_i)$  refer

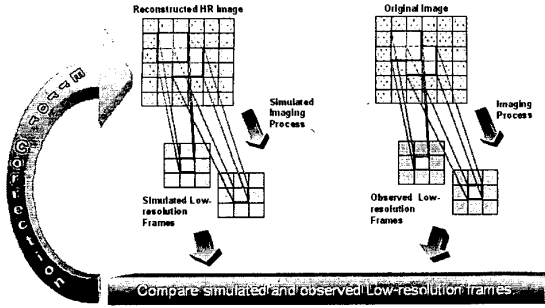


Fig. 3. Schematic Diagram of the Back Projection algorithm.

to lower image frame  $k$  at pixel  $(m_1, m_2)$ . Additional constraint  $C_A$  (bounded amplitude and positivity) can be utilized to improve the results.

Given the above projections, an estimate,  $\hat{f}(n_1, n_2, t_r)$ , of the HR image  $f(n_1, n_2, t_r)$ , is obtained iteratively from all LR images  $g(m_1, m_2, k)$  where constraint sets can be defined as

$$\hat{f}_{l+1}(n_1, n_2, t_r) = T_A \tilde{T} [\hat{f}_l(n_1, n_2, t_r)] \quad l=0,1,2, \quad (8)$$

where  $T_A$  is the relaxed projection operator of  $C_A$  and  $\tilde{T}$  denotes the composition of the relaxed projection operators onto the family of sets  $C_{lr}(m_1, m_2, k)$ .

The initial estimate  $\hat{f}_0(n_1, n_2, t_r)$  is obtained by bilinearly interpolating one of the LR images to HR image and then motion compensating.

In theory, the iterations continue until an estimate lies within the intersection of all the constraint sets. In practice, however, iterations are generally terminated according to a certain stopping criterion such as visual inspection of the image quality, or when changes between successive estimates, as measured by some metric (i.e.,  $\|\hat{f}_l - \hat{f}_{l-1}\|$ , using the  $L_2$  norm), fall below a preset threshold. POCS is an image domain method that offers the flexibility of space-varying (pixel-by-pixel) processing. Later Eren et alii [9] have proposed a robust, object-based SR reconstruction using POCS framework. The proposed method employs a validity map and/or segmentation map. The validity map disables projections based on observations with inaccurate motion information for robust reconstruction in the presence of motion estimation errors; while segmentation map enables object-based processing where more accurate motion models can be utilized to improve the quality of the reconstructed image.

2) *Simple Back-Projection*: This iterative process was initially ideated by Michal Irani and Schmucl Peleg [11], [12]. This technique uses averaged projections in HR grid to iteratively solve the HR image.

This algorithm considers also translational and rotational motion between LR frames.

The approach of back projection method is based on the comparison between the known low-resolution frames and the simulated low-resolution frames, resulting from the computed high-resolution image. At the same of Computer-Aided-Tomography (CAT), HR images are reconstructed from their projections in many directions. The low-resolution pixel is a "projection", in HR grid, of a region in the scene whose size is determined by the imaging blur.

The imaging process, yielding the observed image sequence  $\{g_k\}$ , is modelled by:

$$g_k(m, n) = \sigma_k(h(f(x, y)) + \eta_k(x, y)), \quad (9)$$

where

- $g_k$  is the  $k$ -th observed image frame;
- $f$  is the original scene;
- $h$  is the blurring operator;
- $\eta_k$  is an additive noise term;
- $\sigma_k$  is a non-linear function that digitizes and decimates the image into pixels and quantizes the resulting pixels values from intensities into gray levels.  $\sigma_k$  also includes the displacement of  $k$ th the frame;
- $(x, y)$  is the center of the receptive field (in  $f$ ) of the detector whose output is  $g_k(m, n)$ .

Starting with an initial guess  $f^{(0)}$  for the high-resolution image, the imaging process is simulated to obtain a set of low-resolution images  $\{g_k^{(0)}\}$  corresponding to the observed input image  $\{g_k\}$ . If  $f^{(0)}$  were the correct high-resolution image, then the simulated low-resolution frames  $\{g_k^{(0)}\}$  should be identical to the observed  $\{g_k\}$ . The difference images  $\{g_k - g_k^{(0)}\}$  are then computed and used to improve the initial guess by "back-projecting" each value in the difference images onto its receptive field in  $f^{(0)}$ . The process is repeated iteratively to minimize the error function:

$$e^{(n)} = \sqrt{\sum_k \sum_{(x,y)} (g_k(x, y) - g_k^{(n)}(x, y))^2} \quad (10)$$

In Fig. 3 it is shown schematically the main steps of such techniques. The imaging process of  $g_k$  at the  $n$ -th iteration is simulated by:

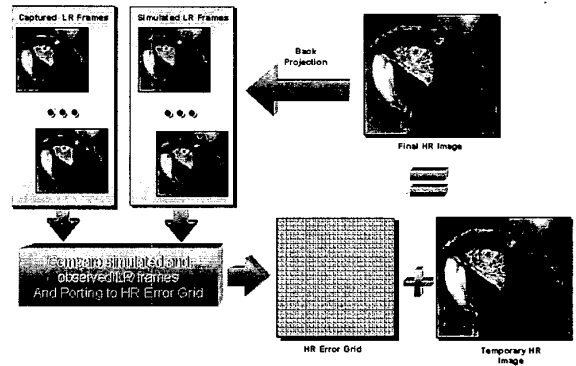


Fig. 4. Classical IBP Block description.

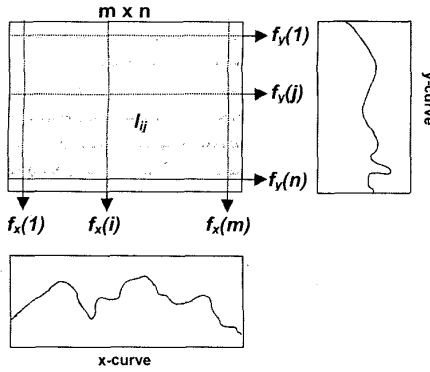


Fig. 5. Image frame alignment along horizontal and vertical direction by using 1-dimensional characteristic.

$$g_k^{(n)} = T_k(f^{(n)} * h) \downarrow s \quad (11)$$

where  $\downarrow s$  denotes a downsampling operator by a factor  $s$ , and  $*$  is the convolution operator. The iterative update scheme of the high-resolution images is expressed by:

$$f^{(n+1)} = f^{(n)} + \frac{1}{K} \sum_{k=1}^K T_k^{-1}(((g_k - g_k^{(n)}) \uparrow s) * h^{BP}) \quad (12)$$

where  $K$  is the number of low-resolution frames,  $\uparrow s$  is an upsampling operator by a factor of  $s$ , and  $h^{BP}$  is a “back-projection” kernel, determined by  $h$  and  $T_k$ . The mean value taken in this last equation reduces additive noise. In Fig. 4 is shown a block description of Irani-Peleg approach.

#### D. Motion Estimation

There are different methods to estimate inter-frames displacement [4], [8], [13], [14], [18], some of them are computationally expensive and involve too much parameters (for translation, rotation, pan, tilt, and zoom), like “Video Orbits” presented by Mann and Picard [14]. To speed up real-time image registration only translational parameters are considered.

In our approach we use the algorithm described by Kim and Koo [13]. In this work authors have proposed an Image resolution enhancement algorithm based on extracting 1-dimensional characteristic curves from subsequent frames with sub-pixel displacement values. This 1-dimensional algorithm is simple and cost-effective, and can be easily applied in real-time processing. In Fig. 5 is represented the extraction process of 1-dimensional characteristics curves from a LR image.

Other kind of motion estimation algorithms could be used. The choice of displacement registration algorithm is strictly constrained by device capabilities and available resources.

### III. PROPOSED ALGORITHM

In order to generate the final HR image, a set of LR frames is acquired. Let  $\{g_k(i,j) \mid k=1,2,\dots,N; i=1,2,\dots,H; j=1,2,\dots,V\}$  be the set of LR frames, where  $N$  is the number of LR available frames,  $H$  and  $V$  are the horizontal and vertical size of LR images respectively.

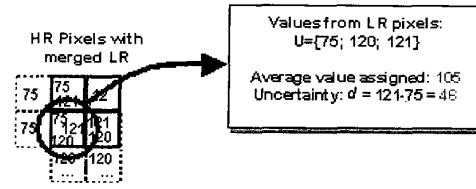


Fig. 6. Example of sub-pixel uncertainty degree estimation.

For every pixel of the LR frame  $g_k(i,j)$  a suitable displacement vector  $\gamma_k(i,j)$  is computed and is used to find the real position of each LR pixels in the HR grid. To improve resolution by an integer factor  $M$  in both horizontal and vertical directions, each pixel  $g_k(i,j)$  is positioned using the vectors  $\gamma_k(i,j)$  in a subpixel  $M \times M$  matrix over the HR-grid. For all HR-grid subpixels, a set  $U(i',j')$  (where  $i'=1,2,\dots,H \cdot M$ ,  $j'=1,2,\dots,V \cdot M$ ) of almost  $N$  values coming from LR frames, is then collected. The first “draft” HR image is constructed using for each pixel  $HR_0(i',j')$  the average of the values contained in the corresponding set  $U(i',j')$ .

An *uncertainty degree*  $d \geq 0$  is associated to each HR subpixel. Depending on  $d$  values the algorithm selects the areas of the real scene that must be effectively improved. In our experiments we have chosen

$$d(i',j') = \max(U(i',j')) - \min(U(i',j')), \quad (13)$$

where  $i'=1,2,\dots,H \cdot M$ ,  $j'=1,2,\dots,V \cdot M$  (See Fig. 6). The use of subpixel *uncertainty degree* together with a few back-projection steps for error estimation, allows reducing the number of computation and iterations without affecting the final quality of the reconstructed image.

Further minimization of processed pixels is obtained by fixing the following threshold values:

- $T$  that represents the minimum amount of admissible *uncertainty*;
- $S, L$  used to discard pixels in too *dark/light* regions [11], [17].

In our experiments the following gray levels threshold ranges were derived empirically:  $T \in [4,6]$ ,  $S \in [5,6]$ ,  $L \in [225,230]$ . The IBP is improved updating each sub-pixel value by properly using errors  $E = \{E_1, E_2, \dots, E_j\}$  already computed in its neighbourhood (See Fig. 7). This approach, named *Auto-Iterative*, converges quicker than classical IBP methods.

Several heuristics using different approaches have been performed in order to determine the “optimum strategy”, involving *Local minimum Error*, *Local Average Error*, *Local Median Error*, etc.. Each pixel neighbourhood error, in HR grid location  $X$ , is the average of differences between the down-sampled HR pixel value ( $G_X \downarrow M$ ) and its corresponding

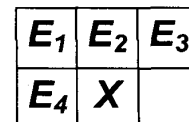


Fig. 7. Example of neighborhood used in Auto-Iterative approach.

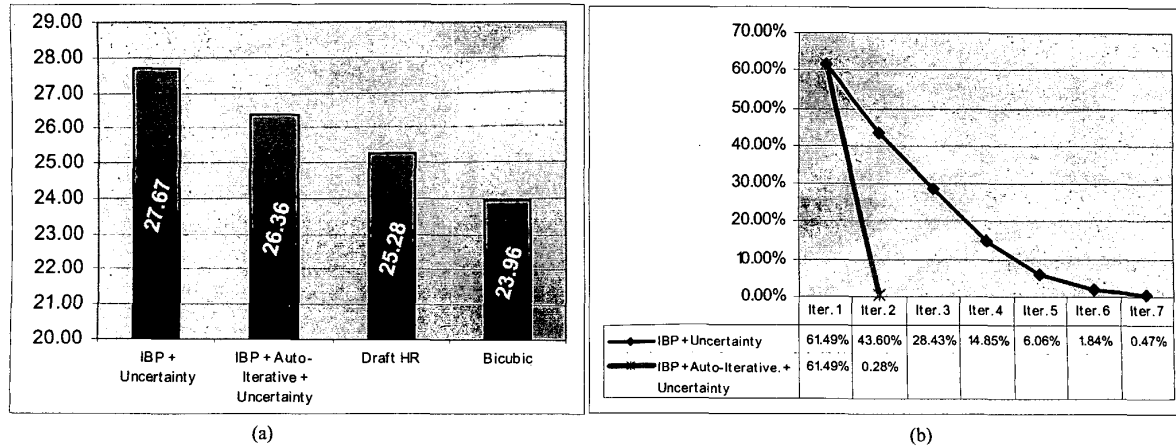


Fig.8. Experimental results on an input sequence of 5 down-sampled and randomly shifted frames: a) PSNR results. The various bins of the histogram show the measured PSNR on i) IBP with uncertainty optimization; ii) IBP with both Auto-iterative and Uncertainty; iii) first "draft" HR image; iv) simple bicubic zooming of one of the LR frames. b) The plot shows (graphically and numerically) the number of improved/corrected pixels at each iteration using the two proposed heuristics.

shifted LR pixels ( $g_{k,y_{1,x}}$ ), that is:

$$E_x = \frac{1}{N} [(G_x \downarrow M) - g_{k,y_{1,x}}] \quad (14)$$

#### IV. EXPERIMENTAL RESULTS

Experiments were accomplished in two successive steps. First of all, in order to tune properly the various parameters of the algorithm, a simulated imaging acquisition process have been used to artificially generate several input sequences. After that, the proposed approach has been tested on real sequences acquired by a CCD camera sensor.

In both cases the LR sequences have been aligned properly using global motion estimation [13].

In Fig. 8 are shown the experimental results on a sequence of artificial LR images. It is possible to observe that the number of iterations is drastically reduced when the local error improvement approach is used (Fig. 8b).

The Peak Signal to Noise Ratio (PSNR) between the original HR image and the final image obtained using the various introduced heuristics shows as our approach is the best trade-off between number of iterations vs. final quality. A good PSNR with few iterations rather than the best PSNR with several iterations is preferred (Fig. 8a). The Auto-Iterative approaches converge quickly compared to classical IBP. Each iteration induces corrections of a certain amount of pixels. The number of corrected pixels at first iteration is always inferior to 60%, as shown in Fig. 8b.

The proposed method has been also tested with a variety of real sequences and simulated down-sampled sequences. In Fig. 9 is shown the outcome of experiment on 5 down-sampled frames. Fig. 10 shows the output of our method applied on a sequence of 3 LR frames, acquired by a CCD end user camera; this example clearly provides evidence of the improved resolution.

#### V. CONCLUSION AND FUTURE WORKS

A series of adaptive techniques able to enhance the resolution of digital images have been presented. The proposed approach extends the classical IBP process by introducing local considerations about uncertainty and error improvement. Experimental results show the effective improvement both for artificial and real LR sequences.

Future works aim to include blurring consideration and more robust motion estimation [4], [8], [18].

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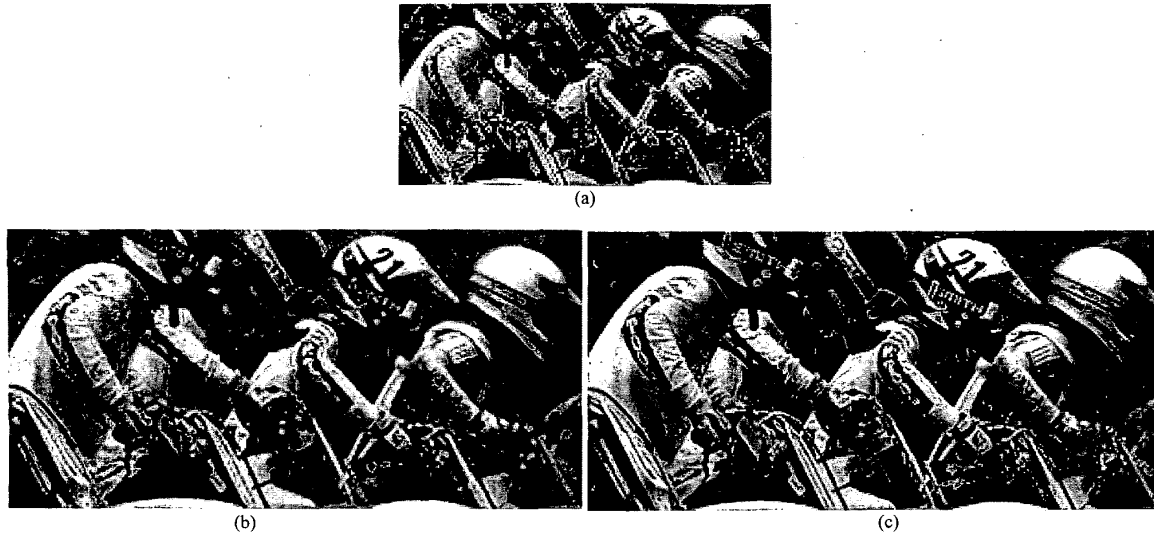


Fig. 9. Results: a) One of the down-sampled frames; b) Zoomed image through Bicubic Algorithm; c) Enhanced image with IBP + Uncertainty + Auto-Iterative.

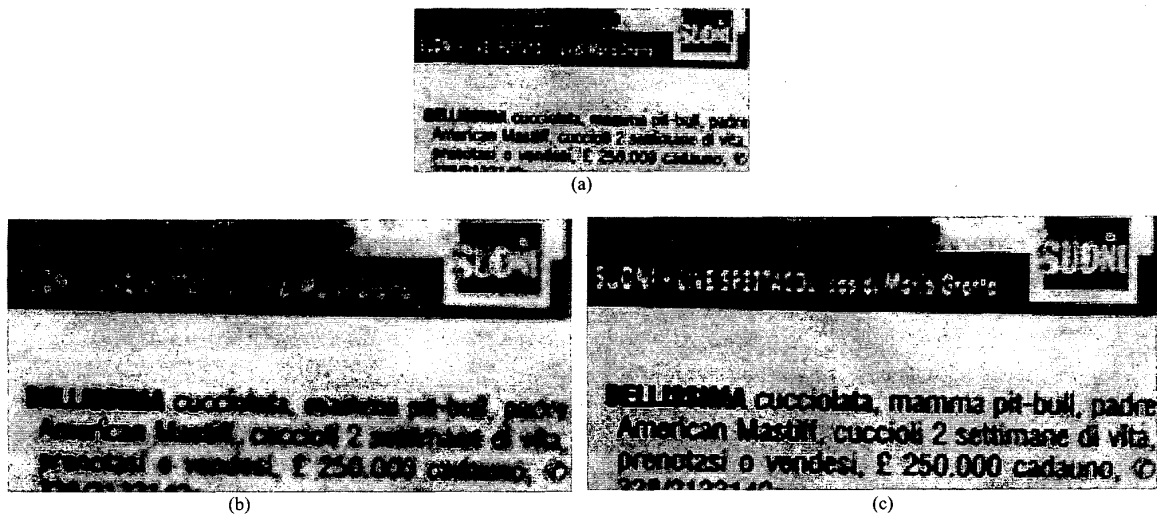


Fig. 10. Resolution Enhancement of a real captured sequence (VGA format with CCD sensor): a) Detail of one of the original LR frames; b) Detail of a zoomed LR image through Bicubic Algorithm; c) Detail of High-Resolution image with IBP + Auto-Iterative + Uncertainty.

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