A ROBUST METHOD FOR BLIND DECONVOLUTION OF BARCODE SIGNALS AND NONUNIFORM ILLUMINATION ESTIMATION

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ABSTRACT
This paper deals with a joint nonuniform illumination estimation and blind deconvolution for barcode signals. Such optimization problems are highly non convex. A robust method is needed in case of noisy and/or blurred signals and nonuniform illumination. Here, we present a novel method based on a genetic algorithm combining discrete and continuous optimization which is successfully applied to data with very strong noise and blur.

Index Terms— Blind deconvolution, nonuniform illumination, barcode restoration, non convex optimization, genetic algorithms.

1. INTRODUCTION
This paper is devoted to the problem of blind deconvolution of linear barcode signals. Linear barcodes are one of the oldest technologies related to automatic identification and data capture. Typical barcodes symbologies are UPC/EAN/JAN and is one variation of over 250. Linear barcodes are a graphical representation of a finite sequences of digits. Information is encoded in the widths (lines) and the spacings of parallel lines. Up to a chosen symbology, each sequence of digits admits a unique graphical representation. So, retrieving digits from an acquired barcode requires accurate estimation of the true length bars and spaces pattern. In order to help decoding, some symbology may include special start/stop group of bars and a validation checksum digit.

Ideally, the barcode is given as a binary one-dimensional signal when scanned by a laser, or a binary image when scanned by a camera.

Linear barcodes are optimized to be read by a laser scanner. Typically UPC, EAN, JAN symbologies have been widely adopted in industrial applications (supermarket checkout system, labelling railroad cars, ...). Nowadays, every article has its own printed barcode. One may imagine using barcodes for its own purpose, for example price comparison, allergen database (gluten, peanut ...). Unfortunately, it is not usual to have its own personal barcode readers.

So, computer vision based barcode recognition could be an interesting alternative. Here, the problem could be separate in two steps: localization and decoding. Computer approach increases the performance of both steps, barcode localization and decoding (see [1, 2]). In the computer vision approaches, low cost cameras (webcam, camerasephone, ...), without autofocusing or macro mode, could introduce some distortions and noise artifacts. As a consequence, decoding performances depend on the distance to the camera to the surface where the barcode appears ([3]).

Anyway, acquired images are often blurred and distorted by various factors, including speckle noise, ambient light. Then, a way, to decode barcodes included in an image, is first to restore it. We would like to retrieve a barcode image from a blurred one acquired by a low cost camera. More real barcode images are also usually distorted by nonuniform illumination. To reduce this problem, in [4], the author proposes some additional hardware device to overcome this drawback, but not convenient in the context of a mobile phone with a digital camera [5]. To consider the effect of nonuniform illumination, several methods have been proposed, among them the illumination cone method, a spherical harmonic based representation ([6]), quotient based image based approaches ([7]) and correlation based method ([8]). The performance of these methods are poor and many of them require either knowledge of light source or a large number of training data which is not tractable in real world applications.

Generally speaking, an image $u$ could be seen as the product of a reflectance $R$ and the illumination effect $I$ ([9]). This model has been used in [10] to deblur barcode signals under nonuniform illumination. The blurring operator is a Gaussian function with unknown standard deviation. The solution is estimated by a penalized non linear least square objective function, based on a proper parametrization of a linear barcode and nonuniform illumination. The solution is then estimated by the well-known gradient based method.

In this paper, we proposed a novel method for blind deconvolution of barcode signals in the out-of-focus case, based on a genetic algorithm taking into account the highly non con-
2. THE MATHEMATICAL MODEL

2.1. A mathematical definition for a barcode

Here, we give a general definition of a barcode in the bidimensional case. We suppose that \( f(x, y) \) is a 2D continuous function representing the intensity value of the barcode at location \((x, y)\):

\[
f(x, y) = \begin{cases} 1, & \text{if } (x, y) \in B_k \\ 0, & \text{else} \end{cases} \tag{1}
\]

where \(B_k\) represents the region bounded by the \(k^{th}\) bar. Assume that \(I_d(i, j)\) is a discrete function acquired from \(f(x, y)\) such that:

\[
I_d(i, j) = \int_j^{j+1} \int_i^{i+1} f(x, y) \, dx \, dy \tag{2}
\]

where \((i, j) = (0, 0), (0, 1), ..., (1, 0), ..., (N, M)\). \(I_d(i, j)\) is the area of the region in pixel \((i, j)\) bounded by the bar passing through that pixel, each pixel is considered as a square region.

2.2. The blurring model

Let \(u \in \mathbb{R}^{NM}\) be an original \(N \times M\) gray-scale image, and \(K \in \mathbb{R}^{NM \times NM}\) represents a blurring (or convolution) operator, \(I \in \mathbb{R}^{NM}\) the non uniform illumination, \(n \in \mathbb{R}^{NM}\) the additive noise, and \(u_0 \in \mathbb{R}^{NM}\) an observation which satisfies the relationship:

\[
u_0 = IKu + n.
\]

In general, the blurring operator \(K\) is supposed shift-invariant, and takes the following form:

\[
K = k \ast u, \tag{3}
\]

where \(k\) is the point spreading function (PSF). In many real cases, the blurring operator \(K\) is unknown. Usually, we assume that \(K\) could be represented by few parameters \(p\), these parameters are \textit{a priori} unknown. For example, in the out-of-focus case, the PSF could be approximated as:

\[
k(x, y) = \frac{1}{\pi r^2} \mathbb{I}_{B_r}(x, y), \tag{4}
\]

where \(B_r\) is the ball with the center 0 and radius \(r > 0\) and \(\mathbb{I}_{B_r}(x, y)\) defines its indicator function.

The non uniform illumination, \(I\), is also unknown. Generally, it is assumed smooth and could be modelled by using B-spline functions that are uniformly located in the spatial domain ([10]):

\[
I(x, y) = \sum_{i=1}^{L_x} \sum_{j=1}^{L_y} I_{ij} \beta^n(x - l_i) \beta^n(y - l_j), \tag{5}
\]

where \(\beta^n(t)\) is a \(n^{th}\) order B-spline function centered at zero, \(L_x\) (resp. \(L_y\)) is the number of the B-spline functions, \(I_{ij}\) the B-spline coefficients and \(l_i, i \in \{1, ..., L_x\}\) (resp. \(l_j, j \in \{1, ..., L_y\}\)) denote uniformly distributed center locations of the B-spline functions.

2.3. The inverse problem

If we suppose that \(n\) is a gaussian noise, the joint estimation of the blur kernel, the illumination and the restored image is an ill-posed problem on \(K, I\) and \(u\). An approximation of \(u, I\) and \(K\) could be obtained by solving the following non convex optimization problem:

\[
\min_{r, I, u} E(r, I, u) = \int_{\Omega} |IK(r)u - u_0|^2 \, dx \, dy \tag{6}
\]

In order to control the noise, a regularization term of the type \(\lambda \int_{\Omega} \varphi(|\nabla u|) \, dx \, dy\) must be added to the cost function \(E\). Yet, the choice of the function \(\varphi\) must be relevant and is often a difficult task.

3. SOLVING THE INVERSE PROBLEM

As seen above, the solution of the inverse problem depends on the regularization term. The method of genetic algorithms is used here to overcome this drawback and to solve the inverse problem on a robust way with respect to noise and blur.

3.1. The algorithm

Genetic algorithms are global optimization methods directly inspired from the Darwinian theory of evolution of species ([11]). They consist in following the evolution of a certain number \(N_p\) of possible solutions, also called population. To each element (or individual) \(x_i \in \mathcal{O}\) of the population is affected a fitness value inversely proportional to \(J(x_i)\), in case of a minimization problem for the cost function \(J\). The population is regenerated \(N_g\) times by using three stochastic principles called selection, crossover and mutation, that mimic the biological law of the survival of the fittest.

They have show their efficiency in many applicable fields, in engineering science or in medicine, cite for instance, car shape optimization [12], turbine shape optimization [13], pacemaker optimization [14], to mention some results obtained by one of the author.
The genetic algorithm that is used here acts in the following way: at each generation, \( \frac{N_p}{2} \) couples are selected by using a roulette wheel process with respective parts based on the fitness rank of each individual in the population. To each selected couple, the Darwinian principles, namely crossover and mutation, are then successively applied with a respective probability \( p_c \) and \( p_m \). A one-elitism principle is added in order to be sure to keep in the population the best element of the previous generation.

### 3.2. The cost function

The cost function that has been used is different from the one written in (6) because the regularization term has been removed and the \( L^2 \) norm is replaced by the \( L^4 \) norm:

\[
\min_{r, I, u} J(r, I, u) = \int_{\Omega} |IK(r)u - u_0|^4 \, dx \, dy. \tag{7}
\]

Here, the choice of the \( L^4 \) norm is not crucial but it has shown better convergence properties.

### 3.3. The search space

One key feature of genetic algorithms is ability to deal, either with discrete or continuous search spaces, or even with both of them. It is precisely the case here as the search space for \( u \) is of finite type whereas the search space for \( I \) and \( r \) is of continuous type:

- **(i) The search space for \( u \):**
  - Discretization to 61 integer values, gathered in a vector \( U = (U_1, \ldots, U_{61}) \in \mathbb{N}^{61} \)

![Fig. 1. The discrete search space for \( u \)](image)

First of all, note that the search of \( u \) is a 1d problem because of the rectangular shape of the bar code. Moreover, in this work, a particular symbology of barcode has been studied, namely the EAN13 type, which is currently the most used one. It encodes 13 characters by using the width of 30 vertical bars. However, the chosen approach can easily adapt to any other type of barcode. As shown in Figure 1, the signal \( u \) to be found is thus discretized in 61 integer values, gathered in a vector \( U \):

\[
U = (U_1, \ldots, U_{61}) \in \mathbb{N}^{61}
\]

which corresponds to the interval lengths (in terms of pixels) of each successive sequence of white and black colors (where \( u \) is respectively chosen equal to 0 and 1). Note in particular that \( U_1 \) and \( U_{61} \) play a particular role because they correspond to the left, respectively right, unknown margin at each side of the barcode in the image. Note also that the constraint

\[
\sum_{i=1}^{61} U_i = M \tag{8}
\]

where \( M \) is the width of the image has to be fulfilled.

- **(ii) The search space for \( r \) and \( I \):** it is a given interval of \( \mathbb{R}_+ \) for \( r \) whereas it is an hypercube included in \([0, 1]^{L_x} \), for \( I \). The latter corresponds to the ordinates of \( L_x \) points used for the reconstruction of \( I \) by cubic splines interpolation.

### 3.4. The darwinian principles

The darwinian principles, namely crossover and mutation, play a crucial role in the convergence properties of genetic algorithms and have to be chosen with care.

- **(i) The darwinian principles for \( u \):** the crossover principle between two vectors \( U \) and \( V \) in \( \mathbb{N}^{61} \) is inspired from the original crossover in the case of chromosomes: it consists in creating two offsprings, \( U' \) and \( V' \) by exchanging a given number, \( m \), of randomly chosen consecutive sequences of each vector (\( m \)-point crossover). As the obtained offsprings \( U' \) and \( V' \) do not generally satisfy the constraint (8), a renormalization principle is added which consists of increasing (or reducing) the value of randomly chosen components of \( U' \) and \( V' \). Such process actually acts as the mutation operator.

- **(ii) The darwinian principles for \( I \) and \( r \):** it consists of a barycentric combination for crossover and a non uniform mutation (see [12] for more details).

### 4. RESULTS

An example of blind deconvolution of a barcode signal is presented here. It corresponds to the deblurring of the signal \( u_0 \) defined on 494 pixels and depicted on Figure 2. As it can be observed, it is an example of a signal, with a strong noise and blur and with a nonuniform illumination. It is representative of the robustness and accuracy of our algorithm for deblurring and denoising. Obviously similar results can be reproduced with any similar signal.

The genetic algorithm presented in the previous section is applied with the following parameters:

\[
(N_p, N_g, p_c, p_m) = (2000, 150, 0.8, 0.5)
\]

Concerning the search domain, no hypothesis is assumed on the localization of the barcode in the image. Value of the out of focus radius is supposed to lie between the values 4 and 7.
Fig. 2. The observed signal $u_0$

(a) The observed barcode
(b) The restored and decodable barcode 4747379384732

Fig. 3. Comparison of the observed and restored barcode.

whereas the illumination variable $I$ is built by using a 5 points cubic spline interpolation.

After the optimization process, the obtained barcode, shown at the bottom of figure 3 and compared with the observed one at the top of the same figure, has been successfully decoded and is associated to the code 4747379384732.

A statistical study on a large number of barcodes has also been done, showing that this approach can give positive results, that is a decodable barcode, on a large range of similar signals, even with a very strong noise (and/or) blur and with nonuniform illumination.

5. CONCLUSION

A robust method for blind deconvolution of barcode signals in the presence of blur, noise and with nonuniform illumination is presented here. Based on the resolution of the associated inverse problem with genetic algorithms on a mixed search space, it allows to decode in a robust and reproducible way, a very noisy and blurred barcode image.

6. REFERENCES