VIDEO SUPER-RESOLUTION WITH FAST DECONVOLUTION*

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Super-resolution problem is posed as an inverse deconvolution problem. Fast non-iterative super-resolution algorithm based on this approach is suggested. Different super-resolution problem statements for the cases of exactly and inexactly known transform operator were considered.

Introduction

The problem of super-resolution (SR) is to recover a high-resolution image from a set of several degraded low-resolution images. This problem is very important in human surveillance, biometrics, etc. because it can significantly improve image quality.

There are two groups of video SR algorithms: learning-based and reconstruction-based. Learning-based algorithms enhance the resolution of a single image using information on the correspondence of sample low- and high-resolution images. Reconstruction-based algorithms use only a set of low-resolution images to construct high-resolution image. More detailed introduction into video SR problems is given in [1], [2].

The majority of reconstruction-based algorithms use camera models [3] for downsampling the high-resolution image. The problem is posed as a set of equations

$$A_k z = u_k, \quad k = 1,2,\dots,N, \tag{1}$$

where z is reconstructed high-resolution image, u_k is k-th low-resolution image, A_k is a downsampling operator which transforms z to u_k, N is a number of low-resolution images. The operator A_k can be generally

* The work was supported by federal target program "Scientific and scientific-pedagogical personnel of innovative Russia" in 2009-2013 and by grant RFBR 09-01-92474-MHKC

represented as $A_k z = DH_{cam}F_k H_{atm} z + n$ [3], where H_{atm} is atmosphere turbulence effect, F_k is a warping operator like motion blur or motion deformation, H_{cam} is camera lens blur, D is a decimation operator, n is a noise. We model H_{atm} and H_{cam} as a single Gauss filter H, and the operator A_k takes the form

$$A_k z = DF_k Hz. \tag{2}$$

Warping operator F_k can be calculated, for example, using motion calculation in base points and interpolation in other points [4], [5]. Variational optical flow estimation approaches are also widely used (see [6], [7], [8], [9]).

Problem definition

We consider the superresolution problem (2) for z and u_k given on the discrete set $\Omega = \{(i, j) : i, j \in Z\}$. Warping operator F_k is modeled as a set of correspondences between coordinates of points of source and warped image $F_k : (\tilde{x}^k_{i,j}, \tilde{y}^k_{i,j}) \leftrightarrow (i, j)$, $(F_k z)(i, j) = z(\tilde{x}^k_{i,j}, \tilde{y}^k_{i,j})$. The operator D performs scaling $(Dz)(x, y) = z(sx, sy)$, where s is the scaling factor. Combination of F_k and D results in

$$(DF_k z)(i, j) = z(\tilde{x}^k_{si,sj}, \tilde{y}^k_{si,sj}) = z(x^k_{i,j}, y^k_{i,j}). \tag{3}$$

Here we renamed $(\tilde{x}^k_{si,sj}, \tilde{y}^k_{si,sj})$ as $(x^k_{i,j}, y^k_{i,j})$.

The image z is defined on discrete set (i, j), but the coordinates $(x^k_{i,j}, y^k_{i,j})$ are not grid points, so we use operator H for both filtering and interpolation:

$$Hz(x, y) = \frac{\sum_{(i,j)} z(i, j) e^{-\frac{(x-i)^2+(y-j)^2}{2\sigma^2}}}{\sum_{(i,j)} e^{-\frac{(x-i)^2+(y-j)^2}{2\sigma^2}}}, \tag{4}$$

where σ is chosen in accordance with scale factor s. We use $\sigma = 0.4\sqrt{s^2 - 1}$.

The problem (1) does not have a solution in most cases. We replace it with an error minimization problem

$$z_R = \arg\min_z \sum_{k=1}^{N} \left\| A_k z - u_k \right\|_2^2, \tag{5}$$

where $\| \cdot \|_2$ is standard Euclidian norm.

Using the notation (3), operator $A_k z$ (2) takes the form

$$(A_k z)(i,j) = Hz(x_{i,j}^k, y_{i,j}^k),$$

and the super-resolution problem (5) takes the form

$$z_R = \arg\min_z \sum_{k=1}^{N} \sum_{(i,j)} \left| Hz(x_{i,j}^k, y_{i,j}^k) - u_k(i,j) \right|^2 . \quad (6)$$

By changing multiple indexes with single index, we rewrite the formula (6) and define the problem as

$$z_R = \arg\min_z \sum_n \left| Hz(x_n, y_n) - w_n \right|^2 . \quad (7)$$

The problem (7) is ill-posed, so regularization methods [10] are used:

$$z_R = \arg\min_z \left(\sum_n \left| Hz(x_n, y_n) - w_n \right|^2 + \alpha\Omega[z] \right) \quad (8)$$

with a stabilizer $\Omega[z]$. Iterative method for solving (8) is discussed in [2]. In this paper, a non-iterative algorithm for solving (7) is proposed.

Adaptive deconvolution

We consider the problem of deconvolution on discrete 1D set for Gauss filter G

$$G(i) = \frac{1}{\sigma\sqrt{2\pi}} \exp(-\frac{i^2}{2\sigma^2}) .$$

The discrete convolution looks as

$$v = Hz = z * G,$$

$$v(i) = \sum_{j=-\infty}^{+\infty} z(j) G(i-j) .$$

The problem of deconvolution is to reconstruct z from given convolution result $v = Hz$

$$z = H^{-1} v .$$

Inverse operator H^{-1} can be constructed using Fourier transform: $\hat{v} = \hat{z}\hat{G}$, $\hat{z} = \hat{v}/\hat{G}$, and z can be found as a convolution of v with inverse Fourier transform of $1/\hat{G}$. Nevertheless, operator H^{-1} is unbounded in the continuous case. Thus in the discrete case it significantly amplifies noise for a noisy data. To avoid this, we use a finite adaptive filter

$$z = v * C,$$

$$z(i) = \sum_{j=-k}^{j=k} z(j) c_{i-j}, \quad c_j = c_{-j}. \tag{9}$$

Coefficients c_{-j} in (9) are chosen to minimize $\|z - v * C\|_2$. Filter length k is chosen in a way to make deconvolution fast, but precise enough. We use $k = 3$.

In two-dimensional case, we process consequently the rows and the columns of the image.

For given super-resolution problem (5), we convolve low-resolution images with Gauss filter and calculate coefficients c_j from given set of images. We seek for

$$\{c_j\} = \arg\min_C \sum_{k=1}^{N} \|u_k - u_k * G * C\|_2^2. \tag{10}$$

Experiments have shown that adaptive filter (9) does not significantly amplify noise. It depends on given images. If the images are noisy, then filter coefficients are smoothed and noise level does not significantly increase after deconvolution. This also means that regularization term (8) is not necessary because adaptive filter (9) is automatically tuned to noise level.

We have compared adaptive filter with unsharp mask $z = \alpha(v - v * G) + v * G$. Unsharp mask shows practically the same results, but it takes more time to estimate its parameters (α, σ).

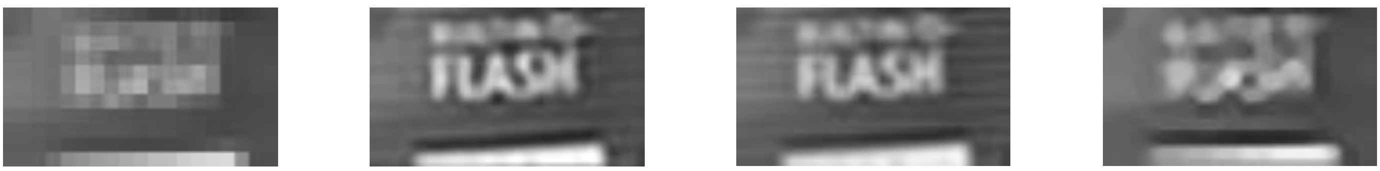
Problem solution

If the points (x_n, y_n) in (7) are grid points, then deconvolution method using adaptive filter can be used. But in general case coordinate values x_n, y_n are not discrete. So, we use the following algorithm:

1. Calculate the values of Hz at all grid points (i, j) using Gauss interpolation (4).

2. Perform deconvolution using adaptive filter.

In Figure 1, the proposed super-resolution method is illustrated for test video sequence in comparison with other image resampling and super-resolution methods.



a) Single frame interpolated b) Regularization-based super- c) The proposed video super- d) Regularization-based single using nearest neighbor method   resolution [2]   resolution method (7).   frame image interpolation [11]

Fig. 1. Super-resolution results using 4 input images and scale factor s=4.

Problem discussion

The proposed super-resolution method (7) shows very good results if the warping operator F_k is calculated precisely. If it has errors, the solution becomes unstable. To avoid this, we pose the super-resolution problem (1) in the presence of errors as follows:

$$z_R = \frac{1}{N}\sum_{k=1}^{N} \arg\min_z \|A_k z - u_k\|_2^2 . \quad (11)$$

We make single-image super-resolution for every image and then calculate an average image.

The approach (11) results in blurred image, but without artifacts caused by warping operator errors.

This approach is illustrated in Figure 2.

a) The super-resolution method (7)   b) Super-resolution for unstable data (10)

Fig. 2. Super-resolution results for 4 input frames and factor s=4 for inexact warping operator.

Conclusion

Fast non-iterative method for image super-resolution has been suggested. The method shows very good results if the warping operator is exactly estimated like in the case of only sub-pixel shifts in the given video sequence. Special version of the super-resolution algorithm has been suggested for the case of inexact warping operator.

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