Super-Resolution Reconstruction of Thermal Infrared Images

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Abstract: In this paper a high-resolution (HR) thermal infrared image is reconstructed from a sequence of subpixel shifted, aliased low-resolution (LR) frames, by means of a stochastic regularized super-resolution (SR) method. The Huber (H) cost function is employed to measure the difference between the projected estimate of the HR image and each LR frame. The bilateral Total Variation (TV) regularization is incorporated as a priori knowledge about the solution. The proposed HTV super-resolution approach that employs the Huber norm in combination with the bilateral TV regularization exhibits superior performance to former SR method. Thus, the effect of outliers is significantly reduced and the high-frequency edge structures of the reconstructed HR thermal infrared image are preserved. The proposed technique is also tested on frames that are corrupted by Gaussian noise and proves superior when compared to existing regularized SR method.

Key-Words: super-resolution, robust estimation, Huber norm, bilateral TV, thermal infrared imaging

1 Introduction

For ecological studies and scientific purposes, the resolution improvement of thermal infrared images is of vital importance. The need for using thermal cameras in applications as the detection of diseases or in finding hidden explosives makes it imperative to reduce their cost. Although advances in sensor technology have led to higher quality thermal images, there are still deficiencies that must be addressed before the particular images could be efficiently used. The present work addresses the issue of the increase in resolution of a thermal infrared image. More specifically, a high-resolution thermal infrared image is created through super-resolution image reconstruction.

Employing signal processing techniques to create an HR image from multiple observed low-resolution ones is called SR image reconstruction. The information related to the relative displacement between the LR images is investigated and spatial resolution is increased by integrating these images into a single one. Simultaneously, the effect of possible blurring and noise in the LR images is also removed. The most important advantage of the specific signal processing approaches is that they are much cheaper than HR imaging equipment. Furthermore, the existing LR imaging systems can still be utilized [1]. Super-resolution image reconstruction methods [2] produce more powerful resolution enhancement results than interpolation techniques that are often met in the literature [3-4].

A stochastic regularized approach to SR image reconstruction is found in the literature [5]. Super-resolution image reconstruction by means of a texture prior is introduced in [6]. A Bayesian regularized approach to the super-resolution problem is also presented in [7]. Another stochastic regularized approach to SR image reconstruction is introduced in [8]. A super-resolution technique that is based on moving least-squares is applied on infrared image sequence in [9]. [10] discusses the applications of SR image reconstruction and deblur filtering to three practical thermal imaging systems. An algorithm that generates shortwave infrared and thermal infrared imagery with a 15m resolution is proposed in [11]. [12] explains in detail how to model SR reconstruction algorithms within existing thermal analysis models such as NVThermIP. Only static background scenarios are treated. A maximum a posteriori (MAP) SR algorithm is presented in [13]. An HR image is created from a set of infrared images obtained by an uncooled infrared detector.

The present work belongs to the category of stochastic, typically Bayesian, regularized approaches to SR image reconstruction. The stochastic regularized super-resolution methods provide stable estimates effectively and distinguish between possible solutions by utilizing a priori image model. A MAP estimation method that copes
with the ill-posed nature of the SR problem is presented. A thermal infrared image is SR reconstructed. The Huber cost function, which is hybrid between quadratic and $L_1$, is employed for the data-fidelity term. The H norm demonstrates robustness when dealing with outliers. The choice of regularization or prior significantly affects the performance of SR algorithms. In this work, the bilateral TV regularizer is added as a penalty factor to the cost function and contributes to edge preservation. So, we present a combination of terms for SR image reconstruction that avoids both erroneous estimates and oversmoothing of the image. An HR thermal image is created from a sequence of subpixel shifted, aliased LR frames. Resolution is increased by a factor of 4. The results of the HTV technique are compared with those obtained by means of the SR technique which is described in [5], in case of noiseless and noisy sequence of frames. The proposed method exhibits greater robustness than the technique in [5] in relation to errors attributed to the assumed model of data and noise.

In Section 2 of this paper, the Huber cost function is discussed. Section 3 contains a detailed description of the SR reconstruction, whereas Section 4 presents the conducted experiments and their results. The conclusions are drawn in Section 5.

2 The Huber Cost Function

Huber estimation is concerned with identifying outliers among data points, giving them less weight. The Huber estimator is essentially the least-squares estimator, but uses the $L_1$ - norm for points that are considered outliers with respect to a certain threshold which is called Huber parameter. The specific parameter determines the influence of the quadratic or the linear region of the H norm. The H function or norm is given by

$$f_{Hb}(x) = \begin{cases} x^2, & \text{for } |x| < \text{hبار} \\ 2\text{hبار}|x| - \text{hبار}^2, & \text{otherwise} \end{cases}$$

(1)

where $\text{hبار}$ is the Huber parameter. It is obvious that for small values the Huber function is quadratic, whereas for larger values becomes linear. The linear growth for large $x$ makes approximation less sensitive to outliers. The Huber norm serves for estimating the difference between the projected estimate of the HR thermal infrared image and each LR frame at the presented regularized approach to SR image reconstruction.

The $L_1$ - norm converges to median estimation [5]. The median and Huber estimators belong to the family of $M$-estimators. Having studied estimators and their influence curves, the $\psi$ - function of a robust $M$-estimator (of the location of a symmetric underlying distribution) should have certain properties [14]. A comparison between the Huber and median estimators, based on the prementioned criteria for $\psi$-function, proves that the Huber estimator predominates over the median estimator. Explicitly, the $\psi$ - function of the Huber estimator is moderately continuous (finite local-shift sensitivity) and is linear at origin, whereas the median estimator $\psi$ - function does not exhibit the specific properties. Thus, Huber estimation leads to more accurate SR reconstruction results than $L_1$ - norm estimation.

3 Super-Resolution Image Reconstruction

3.1 Data-Fidelity Term

Often the imaging system specifications, such as point spread function (PSF) and motion shift, must be either assumed or estimated from the data in order to formulate an image acquisition model. When incorrect estimations exist in the specific model, the data no longer match it, leading to data outliers. When dealing with the SR image reconstruction problem, the effect of outliers has to be reduced. Otherwise, erroneous estimates will be obtained. Therefore, a robust estimator [15] has to be employed for measuring the difference between the projected estimate of the HR thermal infrared image and each LR frame. In the present work the Huber estimator performs the particular task.

The Huber minimization criterion is formulated as follows

$$X = \underset{X}{\text{ArgMin}} \sum_{i=1}^{N} f_{Hb}(DHF_i, X - Y_i)$$

(2)

By means of (1)

$$f_{Hb}(DHF_i, X - Y_i) = \begin{cases} (DHF_i, X - Y_i)^2, & \text{for } \|DHF_i, X - Y_i\| < \text{hبار} \\ 2\text{hبار}|DHF_i, X - Y_i| - \text{hبار}^2, & \text{otherwise} \end{cases}$$

(3)

The operator $F_i$, $i = 1,2,...,N$, stands for translational motion among the LR frames. In fact, a motion vector that determines horizontal and vertical shift corresponds to each frame. The symbol $N$ presents the number of the available frames. Blurring is assumed to result from the same, space-invariant PSF that is represented by the operator $H$. 

\[\text{ISSN: 1790-2769} \quad 41 \quad \text{ISBN: 978-960-474-030-7} \]
regarding all frames. Furthermore, \( D \) stands for the decimation that has been performed on the HR image to be acquired. The matrix \( X \) denotes the desired HR thermal image, while \( Y_i \) denotes the LR frames.

3.2 Regularization Term

Super-resolution image reconstruction is a numerically ill-posed problem. A kind of regularization must be included in the SR formulation so that to stabilize the problem or constrain the space of solutions. Additionally, regularization can serve for removing artifacts from the final answer and realizing considerable speedups in minimization. From a statistical perspective, as is the case in the present work, regularization is incorporated as a priori knowledge about the solution. The bilateral TV regularizer [5] is employed in the present paper. It is given by

\[
Y_{BTV}(X) = \sum_{l=-P}^{P} \sum_{m=0}^{P} a^{l|m} \| X - S_i^{l|m} Y \|_1 \tag{4}
\]

The operators \( S_i^{l|m} \) and \( S_i^{m} \) shift the image \( X \) by \( l \) and \( m \) pixels horizontally and vertically respectively, presenting several scales of derivatives. The weight \( a \) is a scalar taking values between 0 and 1 and gives a spatially decaying effect to the regularization terms summation. The parameter \( P \) determines the size of the regularization kernel.

3.3 Super-Resolution Formulation

Considering the above-mentioned data-fidelity and regularization terms, the SR problem is formulated. A gradient-based method, the steepest descent, is employed to perform the minimization task and regularization terms summation. The parameter \( \lambda \) determines the strength with which the particular penalty is enforced and is called regularization parameter. In relation to the parameter \( \beta \), it is a scalar that determines the step size in the direction of the gradient. The constructed SR algorithm demonstrates reduced sensitivity to outliers.

4 Experimental Procedure and Results

In this section, the performance of the resolution enhancement algorithm that is proposed in the present work is compared to that of an existing resolution enhancement method [5] (Table 1). Experimentation is carried out employing thermal infrared data. To be more precise, super-resolution image reconstruction is applied to one synthesized LR sequence which consists of 20 frames. The original HR file used at the specific controlled simulated experiment has been drawn from a web site and is shown in Fig.1a. At the beginning, in order to simulate the effect of camera PSF, the particular image is convolved with a symmetric Gaussian low-pass filter of size 4x4 and standard deviation equal to 1. The image that results is then downsampled by the factor of 4 in each of the horizontal and vertical directions. The prementioned procedure, preceded by subpixel shifting the HR image in the vertical and horizontal directions employing various motion vectors, is followed to produce 19 LR images from the original scene.

Fig.1b depicts the result of implementing the method that employs the \( L_1 \) - norm in the data-fidelity term and the bilateral TV regularizer in the regularization term. Fig.1c demonstrates the corresponding result of the proposed method. Visual comparison proves the predominance of the HTV technique. In Fig.1b some artifacts are visible at the soldiers body. However, the proposed method avoids the creation of such artifacts. Also, in the image resulting from the \( L_1 \) - norm technique, the car windscreen is coarse. In the image of the proposed method the windscreen seems to be refined. Additionally, the proposed method achieves to reconstruct the tree foliage quite more accurately than the method in [5]. Above observations are clearly discernible in Fig.2. Table 2 contains numerical results regarding
the predefined comparison. According to the “correlation coefficient”, “MSE” and “Xydeas and Petrovich” measures, the HTV technique is superior to the technique in [5]. The experiment is conducted by adding Gaussian noise to each frame, as well. The 2nd corrupted by noise, frame along with the noiseless one are shown in Fig.3. The HTV technique again produces superior results than the $L_1$ – norm technique. Table 3 presents numerical results as far as the noisy experiment is concerned. Consequently, visual and numerical comparisons assert that the H norm estimator is superior to the $L_1$ – norm one.

The selected parameters for the HTV method are $a = 0.2, \lambda = 0.005, \beta = \frac{1}{9}, hubpar = \frac{1.5}{255}$. Additionally, $y$, a regularization kernel of size $P$ equal to 3 leads to results equivalent to those obtained with $P = 2$. Thus, $P = 2$ is employed to reduce computational complexity and avoid time consumption. Furthermore, the image acquisition model that is employed in the present work, assumes that the respective motion of camera and scene is translational. In fact the particular motion is seldom pure translational. However, the HTV method is robust enough to significantly reduce the effect of outliers that are caused by this possibly wrong assumption regarding shifting of frames.

5 Conclusions

In this work a stochastic regularized SR method creates a high-resolution thermal infrared image from subpixel shifted, aliased LR frames. Resolution is enhanced by a factor of 4. The Huber norm is employed for the data-fidelity term. The H cost function is hybrid between quadratic and $L_1$ and demonstrates robustness in presence of outliers. Regularization takes the form of the bilateral TV regularizer and compensates for the missing measurements information. Visual and numerical comparisons prove that the proposed HTV method predominates over former regularized SR approach in the presence of outliers as well as in the reconstruction of edge structures. The proposed method demonstrates superior performance even in case of noisy data set.

References:


[14] J. Tukey, Understanding Robust and
Table 3: Numerical results regarding noisy data

<table>
<thead>
<tr>
<th>Image origin</th>
<th>Correlation coefficient</th>
<th>MSE</th>
<th>Xydeas and Petrovich</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L_1$ norm + BTV</td>
<td>0.9848</td>
<td>8.3182x10^{-4}</td>
<td>0.8717</td>
</tr>
<tr>
<td>Huber norm + BTV</td>
<td>0.9870</td>
<td>7.1318x10^{-4}</td>
<td>0.8884</td>
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</table>

Fig.2a,c) Part of the car windscreen and the soldier resulting from the SR technique in [5]. b,d) Part of the car windscreen and the soldier resulting from the proposed SR technique.

Table 2: Numerical results regarding noiseless data

<table>
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<th>MSE</th>
<th>Xydeas and Petrovich</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L_1$ norm + BTV</td>
<td>0.9548</td>
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<tr>
<td>Huber norm + BTV</td>
<td>0.9799</td>
<td>1.1020x10^{-3}</td>
<td>0.8423</td>
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</table>

Table 1: The different SR problem formulations that are compared in the present paper

<table>
<thead>
<tr>
<th>SR methods</th>
<th>Data-fidelity term</th>
<th>Regularization term</th>
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<tbody>
<tr>
<td>Method in [5]</td>
<td>$L_1$ norm</td>
<td>Bilateral TV</td>
</tr>
<tr>
<td>HTV method</td>
<td>Huber norm</td>
<td>Bilateral TV</td>
</tr>
</tbody>
</table>

Fig.1a) The original HR image. b) The HR image resulting from the SR technique in [5]. c) The HR image resulting from the proposed SR technique. Results regarding noiseless data.

Table 1: The different SR problem formulations that are compared in the present paper

Exploratory Data Analysis, John Wiley & Sons, 1983.