

Impact to formula gradient impulse noise reduction from images

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Abstract

For the majority of image processing techniques and applications, denoising a photo is a must. The Taylor series is used to suggest a new conjugate gradient scalar. Together with the descent property, the novel formula satisfies the convergence properties. Lastly, we provide a few illustrations of picture restoration using the suggested conjugate gradient technique.

Subject Classification: 90C30, 65K05, 49M37.

Keywords: Impact scalar for gradient, Convergence property, Image restoration.

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1. Introduction

Iteration problems may really be used to simplify and solve a number of intricate optimization problems in engineering and management, such as the noisy pixel cleaning model:

$$f_{\alpha}(u) = \sum_{(i,j) \in N} \left[|u_{W,Z} - y_{W,Z}| + \frac{\beta}{2} (S_{W,Z}^1 + S_{W,Z}^2) \right] \quad (1)$$

where $S_{W,Z}^1 = 2 \sum_{(m,n) \in P_{W,Z} \cap N^c} \phi_{\alpha}(u_{W,Z} - y_{m,n})$, $S_{W,Z}^2 = \sum_{(m,n) \in P_{W,Z} \cap N} \phi_{\alpha}(u_{W,Z} - y_{m,n})$, see [1-4]. In terms of image restoration, $y_{i,j}$ is the value of the picture's pixel at position (W,Z) , $\phi_{\alpha} = \sqrt{\alpha + x^2}$ is the parameterized edge-preserving potential function $\alpha > 0$, and β is the parameter when the conditions are satisfied. $u_{W,Z} = [u_{W,Z}]_{(W,Z) \in N}$ is a $|N|$ -length column vector that is lexicographically arranged.

In order to minimization (1), the conjugated gradients technique was used in a manner that:

$$\text{Min} f_{\alpha}(u), u \in R^n \quad (2)$$

$f_{\alpha}(u): R^n \rightarrow R$ is the smooth function. A sort of iterative algorithm, the conjugate gradient technique builds a series using the following format:

$$u_{k+1} = u_k + \alpha_k d_k \quad (3)$$

where the search direction is denoted by d_k and the step size found by a trustworthy precise line search is denoted by α_k , as in:

$$\alpha_k = -g_k^T d_k / d_k^T Q d_k \quad (4)$$

Formula [5], [6] adds information. The formula for determining the step length α_k used in the Wolfe model is as follows:

$$f(u_k + \alpha_k d_k) \leq f(u_k) + \delta \alpha_k g_k^T d_k \quad (5)$$

$$d_k^T g(u_k + \alpha_k d_k) \geq \sigma d_k^T g_k \quad (6)$$

where $0 < \delta < \sigma < 1$. Further niceties may be found in [7-9]. The search direction selection formula for the conjugate gradient technique is as follows:

$$d_{k+1} = -g_{k+1} + \beta_k d_k \quad (7)$$

where β_k is a scalar. instances of different types of scalars the most famous Fletcher-Reeves method [10], [11], as:

$$\beta_k^{FR} = \|g_{k+1}\|^2 / \|g_k\|^2 \quad (8)$$

Convergence characteristics shown by iterative algorithms have been the subject of much investigation. Zoutendijk [12], who first showed the worldwide convergence of the FR technique when precise

line searching was carried out, is considered the originator of these investigations. The conjugate gradient scalar has been the subject of several unique formulas that have been created up to this point. These scalar have great numerical performance and lead to the global solution.

This investigation starts off with an all-new scalar conjugate derivation, then moves on to provide a novel viewpoint on the denominator $d_k^T G v_k$ based on the quadratic model, and then wraps up with an examination of the conjugate gradient approach and an analysis of convergence. After that, the numerical results of the method that was suggested are shown, and they are contrasted with the outcomes of a variety of other conjugate gradient processes.

2. New scalar

One important scalar conjugate in minimization is the iterative approach. We discovered a Taylor series in order to obtain a new scalar conjugate, which is as follows:

$$f(u) = f(u_{k+1}) + g_{k+1}^T(u - u_{k+1}) + \frac{1}{2}(u - u_{k+1})^T Q(u_k)(u - u_{k+1}) \quad (9)$$

By striking $u = u_k$ and find the derivative of (9) as:

$$\nabla f_{k+1} = g_k + Q(x_k)s_k \quad (10)$$

Putting (10) in (9), we get:

$$s_k^T Q(u_k)s_k \quad (11)$$

The new scalar is obtained by utilizing the conjugate condition. Recall that the conjugate condition is given by:

$$s_k^T Q(u_k)s_k = 2(f_k - f_{k+1}) + 2y_k^T s_k + 2g_k^T s_k \quad (12)$$

Combining (11) with (12), we get:

$$\beta_k = \rho_k \frac{g_{k+1}^T y_k}{d_k^T y_k}, \rho_k = 2 + \frac{2(f_k - f_{k+1}) + 2g_k^T s_k}{s_k^T y_k} \quad (13)$$

By using precise line search to the equation above, we obtain:

$$\beta_k = \rho_k \frac{\|g_{k+1}\|^2}{d_k^T y_k}, \rho_k = 2 + \frac{2(f_k - f_{k+1}) + 2g_k^T s_k}{s_k^T y_k} \quad (14)$$

This formula is referred to as the BBL.

3. Global convergence:

Analyzing the algorithm's global convergence properties is the aim of this part. We first make the following:

1. Level set $\Omega = \{u: u \in R^n, f(\cdot, u) \leq f(\cdot, u_1)\}$, $f(u)$ is bounded below.
2. Because the derivative $\nabla f(u)$ is Lipschitz with $L > 0$, all $\tau, v \in R^n$ satisfy the inequality:

$$\|g(\tau) - g(v)\| \leq L\|\tau - v\|, \forall \tau, v \in R^n \quad (15)$$

Theorem 1: *If we make $\{x_k\}$ and $\{d_k\}$ using a new technique, we get:*

$$d_{k+1}^T g_{k+1} < 0 \text{ and } d_{k+1}^T g_{k+1} = \beta_k d_k^T g_k. \quad (16)$$

Proof: Evidently, as $d_k = -g_k$ is necessary for $d_1^T g_1 < 0$. Be for that $d_k^T g_k < 0$ for any k . It may be easily obtained from (7) and (14):

$$\begin{aligned} d_{k+1}^T g_{k+1} &= -g_{k+1}^T g_{k+1} + \beta_k d_k^T g_{k+1} \\ &= -\beta_k \frac{d_k^T y_k}{2 + \frac{2(f_k - f_{k+1}) + 2g_k^T s_k}{s_k^T y_k}} + \beta_k d_k^T g_{k+1} \end{aligned} \quad (17)$$

which guarantees:

$$d_{k+1}^T g_{k+1} = \beta_k [d_k^T g_{k+1} - d_k^T y_k] \quad (18)$$

From (11) and (18) yields the result:

$$d_{k+1}^T g_{k+1} = \beta_k d_k^T g_k \quad (19)$$

Absolutely $d_k^T g_k < 0$, which leads to:

$$d_{k+1}^T g_{k+1} < 0 \quad (20)$$

The proof is complete.

4. Numerical Results

Here, we demonstrate how salt-and-pepper impulse noise (1) may be successfully reduced using the BBL method. The BBL approach uses $\sigma=0.1$ and $\delta=0.001$ as parameters. The research flow diagram may be found in Table 1. The initial test images are displayed in Table 1. For all computer simulations, MATLAB is utilized, [13-20]. Comparisons between the FR technique and performance assessments of the BBL methodologies are provided. It's crucial to remember that the primary objective of this study is to determine how soon carbon emissions may be reduced (1). A measure used to evaluate the fidelity of the reconstructed pictures is the Signal-to-Noise Ratio (*PSNR*):

$$PSNR = 10 \log_{10} \frac{255^2}{\frac{1}{MN} \sum_{W,Z} (u_{W,Z}^r - u_{W,Z}^*)^2} \quad (21)$$

where $u_{W,Z}^r$ and $u_{W,Z}^*$ are the pixel values of the innovative image and the reinstated image, respectively. The ensuing are the conditions that must be met in order to come to a halt in either approach:

$$\frac{|f(u_k) - f(u_{k-1})|}{|f(u_k)|} \leq 0.0001 \text{ and } \|f(u_k)\| \leq 0.0001(1 + |f(u_k)|) \quad (22)$$

The results of examinations are outlined in Table 1, which may be seen below. It comprises the *PSNR*, which is abbreviated as PSNR; the number of iterations, which is abbreviated as NI; and the number of function evaluations (NF).

Table 1
To show the improvement between FR and BBL algorithms.

Image	Noise level r (%)	FR-algorithm			BBL-algorithm		
		NI.	NF.	PSNR (dB)	NI.	NF.	PSNR (dB)
Ho	50	52.	53	30.6845	44	45	34.7377
	70	63.	116	31.2564	49	51	31.1201
	90	111	214	25.287	82	148	25.0197
El	50	35	36	33.9129	36	38	33.8768
	70	38	39	31.864	39	41	31.8006
	90	65	114	28.2019	53	55	25.1477
c512	50	59	87	35.5359	38	45	35.3948
	70	78	142	30.6259	47	53	30.6466
	90	121	236	24.3962	86	164	24.9044
Le	50	82	153	30.5529	62	65	30.4106
	70	81	155	27.4824	68	71	27.421
	90	108	211	22.8583	98	186	22.7652

In terms of comparison the performance of the recommended algorithms is superior than that of the FR technique, as can be seen in the table.

5. Conclusions

We provided a new modified conjugate gradient formula in addition to the new conjugate gradient techniques. To improve the accuracy of our results, this was done. We found the worldwide convergence of the Wolfe line by applying the search criteria. Theoretically, new may drastically lower the number of function evaluations and iterations while maintaining the same level of image quality, according to simulations (See Figure 1).

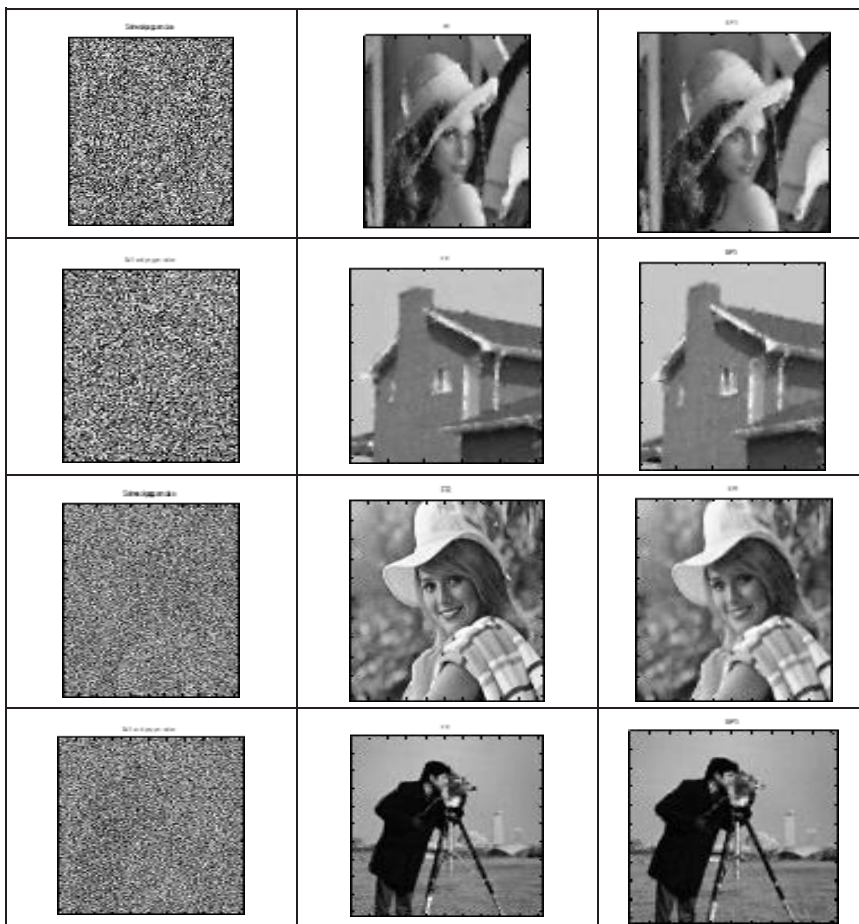


Figure 1
Some cases of images when Noise level (90%)

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Received October, 2024