Super-sparosely view-sampled cone-beam CT by incorporating prior data

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Abstract. Computed tomography (CT) is widely used in medicine for diagnostics or for image-guided therapies, and is also popular in industrial applications for nondestructive testing. CT conventionally requires a large number of projections to produce volumetric images of a scanned object, because the conventional image reconstruction algorithm is based on filtered-backprojection. This requirement may result in relatively high radiation dose to the patients in medical CT unless the radiation dose at each view angle is reduced, and can cause expensive scanning time and efforts in industrial CT applications. Sparse-view CT may provide a viable option to address both issues including high radiation dose and expensive scanning efforts. However, image reconstruction from sparsely sampled data in CT is in general very challenging, and much efforts have been made to develop algorithms for such an image reconstruction problem. Image total-variation minimization algorithm inspired by compressive sensing theory has recently been developed, which exploits the sparseness of the image derivative magnitude and can reconstruct images from sparse-view data to a similar quality of the images conventionally reconstructed from many views. In successive CT scans, prior CT image of an object and its projection data may be readily available, and the current CT image may have not much difference from the prior image. Considering the sparseness of such a difference image between the successive scans, image reconstruction of the difference image may be achieved from very sparsely sampled data. In this work, we showed that one can further reduce the number of projections, resulting in a super-sparse scan, for a good quality image reconstruction with the aid of a prior data. Both numerical and experimental results are provided.

Keywords: Computed tomography (CT), sparse-view CT, total-variation (TV), prior image, compressive sensing (CS), low-dose CT

1. Introduction

Sparse-view CT, which refers to a CT technique that acquires sparsely sampled data in projection angles to reconstruct volumetric images of the scanned object, inspired by a compressive sensing (CS) theory has recently gained researchers’ wide interest. It is considered a significant technological addition, not only to the clinical but also to the industrial applications. Sparse-view CT may provide a viable option for low-dose CT in clinical applications. Typically in diagnostic CT systems, it is difficult if not impossible to switch the beam on-and-off very rapidly. Therefore, lowering mAs has been considered the rule-of-thumb method to achieve low- dose CT [1]. In many other CT systems particularly including
those based on a flat-panel X-ray detector, however, the gantry rotation is reasonably slow and the power-switching accordingly may be relatively straightforward. By reducing the number of views instead of lowering mAs per each view, sparse-view CT can decrease the imaging radiation dose to the patients. In the industrial applications, sparse-view CT technique can be very useful in terms of reducing the scanning time and the detection cost. In addition, an X-ray source array may replace a mechanically scanning prototype CT by electrically switching the source array to scan objects. In such an array system, due to a finite size of the source unit, sparse angular sampling may become a natural choice, and the sparse-view CT subsequently can be implemented.

Image reconstruction from sparse-view data is challenging in general, and many iterative algorithms for sparse-view CT image reconstruction have been proposed and investigated [2–5], which outperform the analytic reconstruction algorithms such as Feldkamp-Davis-Kress (FDK) or other similar algorithms [6,7] to varying degrees. In particular, image total-variation (TV) minimization algorithm based on a compressive sensing theory [8] has shown its excellent performance in sparse-view CT applications.

The TV minimization algorithm exploits the sparsity of image derivative magnitude, via reducing the number of unknowns for a given system of equations, or measurements [9]. Research efforts have additionally been made on improving the algorithm convergence or the convergence speed by use of various optimization techniques [10]. A remarkable boost in computational speed was also made possible by GPU-based implementation of TV minimization algorithm [11]. Sampling conditions necessary for reconstructing images in sparse-view CT have also been addressed and discussed in the context of discrete-to-discrete imaging models with a special interest in the relationship between object sparsity and sufficient sampling condition [12].

In many applications of CT, prior CT projection data of the scanned object may be available. For example, in CT perfusion, consecutive CT scans are conducted to study temporal dynamics of image contrast, naturally producing prior data for the following scans [13]. In image-guided radiation therapy, daily cone-beam CT (CBCT), as a useful tool for accurate patient setup and target localization, provides prior images and projection data for the following days [14]. In an industrial power-plant imaging, mostly interested imaging area is a limited region-of-interest (ROI) outside of which is supposedly stationary, and repeated scans are often necessary to monitor the ROI [15,16]. The initial CT imaging of a power-plant with a full field-of-view may provide the prior image and data of the power-plant for the following ROI scans. These prior images and data can help reducing the radiation dose or scanning time and efforts in each application for the repeated or following scans. Assuming that the prior image is provided in a good quality and that the anatomical or internal structural change between the successive scans is relatively small, one can imagine that the difference image between the successive scans is of sparser distribution of image components than the whole object image. Recalling that the compressive sensing-based techniques such as TV-minimization makes use of the sparseness of a certain type of transform of image and that those algorithms can successfully reconstruct the images from sparse-view data, it is motivated to substantially reduce the number of views for image reconstruction of the difference image in the following scans. The reconstructed difference image can then be added onto the prior image to yield the current image in the following scans.

Prior image knowledge has been utilized in the context of CS in other works, particularly including the algorithm approach referred to as prior-image constrained compressive sensing (PICCS) [4]. The prior image has been used as a constraint to force the current image to be deviated as minimally as possible while the current image sparseness is maximized. In their implementation, the two terms— the sparseness of difference image and the sparseness of current image—are combined with a weighting factor in the objective function, and the optimization of the weighting factor is empirically determined. Our approach
in theory is closely related to the extreme condition of the PICCS that only maximizes the sparseness of difference image. However, practical implementations of the two approaches are different and the two methods can lead to different image reconstructions. The PICCS algorithm uses a discretized prior data from the forward x-ray transform of the voxelized prior image. In contrast, the proposed method uses the prior data from the forward x-ray transform of a continuous prior object. The utilization of a prior image in a discrete domain, as is done in the PICCS approach, may result in a suboptimal image quality due to the approximation involved in the x-ray transform. A comparison study is provided in terms of the effects of using projections from a continuous prior object versus a discrete prior image. It is shown that higher-quality images can be obtained by use of the proposed approach that utilizes projections of a continuous prior object in the super-sparsely view-sampled CT.

2. Methods

In this work, we used a CBCT system that can acquire projection data at predefined angular source positions accurately. Therefore, a repeated scan at sparse views that replicate part of the angular source positions of a previous scan can be achieved. An in depth discussion on the data acquisition part is given in Section IV. In the proposed method, we assumed that an acceptable quality of image can be obtained from a prior scan. It could be an image reconstructed by a conventional analytic algorithm such as FDK algorithm from densely angular-sampled projections. Or, it could be an image reconstructed by an iterative algorithm such as the TV algorithm from sparsely angular-sampled projections. In this work, considering the significance of the application of the proposed algorithm to low dose CT scans, we focus only on the TV algorithm instead of FDK algorithm, considering a potential reduction of dose even in the prior image acquisition. In the following scans, super-sparsely angular-sampled projections are acquired, from which even the TV algorithm may not reconstruct the current image successfully, because the amount of available data is simply too small. However, if the internal anatomical change is relatively small in terms of locality and severity, the difference image between the successive scans can be reconstructed successfully from the subtracted super-sparsely angular-sampled projections between the two scans. We can then add the difference image on to the existing prior image to obtain the current image. The reconstruction process is illustrated by a flow chart as shown in Fig. 1, and the descriptions are as following:

1. At \( t = 0 \), we take first projection data of an object and reconstruct the image as schematically shown in Fig. 2(a) at 360 views. This image is considered as a prior image.
2. Suppose a small change (by adding a circle and triangle in the schematic example shown in Fig. 2) has occurred in the object by the time \( t = \Delta t \). Now, we take super-sparsely sampled projection data \( i.e. \), at only 15 views on regular intervals for example.

3. We then subtract the data acquired at time \( t = \Delta t \) from the data at \( t = 0 \) for the corresponding views, and reconstruct the difference image using the TV minimization algorithm as shown in Fig. 2(c).

4. Finally, we superimpose the difference image on the prior image to get the reconstructed image at \( t = \Delta t \), which would look like the one shown in Fig. 2(b).

In case of repeated scans more than once, one can repeatedly apply the proposed method for the following scans with super-sparse projection data. One can use either the reconstructed image of the previous scan as a prior image or the very first image as a prior image if the change of anatomy is still considerably small. We explain the data subtraction and the image reconstruction for the super-sparsely sampled data below.

2.1. Data subtraction

Suppose \( g_0(\alpha_i, u, v) \) represents the data array of the projection at time \( t = 0 \), where \( u \) and \( v \) are the detector array indices, and \( \alpha_i \) refers to the source angular position in the \( i^{th} \) projection with \( i = 1, 2, \ldots, N_0 \). Similarly, \( g_1(\beta_j, u, v) \) represents the array of the super-sparsely sampled projection data acquired at \( t = \Delta t \), where \( \beta_j \) refers to the source angular position in the \( j^{th} \) projection with \( j = 1, 2, \ldots, N_1 \leq N_0 \). Now, the difference data array \( g \) represents the projection data difference between the two data sets \( g_0 \) and \( g_1 \) collected from each view at \( \beta_j \) with \( j = 1, 2, \ldots, N_1 \). Note that we assumed there always exists \( i \) that satisfies \( \alpha_i = \beta_j \) for each \( j \). Therefore, the difference data can be written as following:

\[
g(\beta_j, u, v) = g_0(\alpha_i, u, v) - g_1(\beta_j, u, v),
\]

with \( \alpha_i = \beta_j \) and \( j = 1, 2, \ldots, N_1 \).

(1)

\( g \) will be used to reconstruct the difference image by the TV minimization algorithm.

2.2. Total-variation minimization algorithm

TV minimization algorithm is an iterative image reconstruction algorithm based on the minimization of the image total-variation subjected to the constraint of data fidelity and image non-negativity [2, 3]. The TV minimization algorithm can reconstruct acceptable quality images from sparse projection views. Here we use it to reconstruct the difference image from the subtracted projection data set that
contains the changes in the image with respect to the prior image. Note that we should remove non-negativity constraint in this case, because the difference image may have negative pixel values as well. The algorithm seeks a solution to the following optimization problem:

$$f_{diff}^0 = \arg \min ||f_{diff}||_{TV} \text{ such that } ||Af_{diff} - g|| < \varepsilon,$$

where $f_{diff}$ represents a difference image under iteration, $f_{diff}^0$ the minimum image TV solution, $A$ the system matrix. $\varepsilon$ is used to keep a balance between a TV-gradient descent step and an ART step. It is important to avoid over-sacrificing data fidelity due to regularizing in the TV step. We empirically found that the value of data distance after 20 iterations of ART steps provides a reasonably robust upper bound of data fidelity in the TV algorithm.

We followed a constrained optimization algorithm to solve Eq. (2) as presented by Sidky et al. [3]. It has two steps. In the first step, algorithm improves the data consistency using ART step. In the second step, optimization is carried out using TV-steepest descent method which takes the derivative of image TV with respect to each pixel values. TV-steepest descent method reduces the TV of the image estimate aiming at the minimum TV image out of the feasible image sets.

Both simulation and experimental studies were performed using the prior data with the TV minimization algorithm to validate the proposed method. A Shepp-Logan phantom was used for the simulation study, and a tube phantom with a micro-CT system was used for the experimental study. We discuss the phantoms and scanning conditions in a separate section.

2.3. PICCS algorithm

PICCS is also based on total-variation minimization and incorporates a discrete prior image to reconstruct a current image from an incomplete data set such as sparsely sampled projections. It is formulated as:

$$\min f \left[ \alpha |\psi_1 (f - f_p)|_{l_1} + (1 - \alpha) |\psi_2 f|_{l_1} \right], \text{ s.t. } Af = Y$$

where $f_p$ is a discrete prior image used to reconstruct the current image $f$. $\psi_1$ and $\psi_2$ are sparsifying transformations and are the image total variation kernel in this work. The system constraints are given by $Af = Y$, where $Y$ correspond to the measured projection data. PICCS consist of two steps. In the first step, current image $f$ is reconstructed using ART in search for a solution to $Af = Y$. In the second step, $l_1 - norm$ of the discrete gradient of the subtracted $(f - f_p)$ and current images are minimized using the standard steepest descent method [4]. PICCS applied the sparsifying transformation to the difference image in the image domain in order to constrain the image under reconstruction to conform the prior image. The objective function in the PICCS approach comprises a combination of sparsifying transformations of the current image estimate and the difference image. A weighting factor $\alpha$ controls the relative contribution of the difference image term, and its determination may be highly task-dependent.

2.4. Numerical phantom

For a numerical study, the Shepp-Logan phantom was used. A modified phantom was also prepared via making a few changes in its ellipsoidal components. Circular cone-beam geometry was simulated, and prior image projection data sets from the original phantom at 360 views on regular angular intervals were acquired. Super-parse projection data were acquired using the modified phantom, at 15 views on regular angular intervals. Projection data of the modified phantom was subtracted from the corresponding views of the original phantom projection data, and the resulting projection data was used for reconstruction of the difference image.
2.5. Tube phantom

To validate our approach experimentally, we fabricated a paraffin-filled tube-phantom with dimensions of 6.0 cm × 3.5 cm × 4.0 cm, as shown in Fig. 3. We name it a tube phantom because it contains three tubes passing through the paraffin-made cylinder. Note that the figure shows the phantom before paraffin molding and after the molding. A few air gaps were also introduced in the paraffin cylinder for better simulating the cavities of a small animal. A micro-CT system (Polaris-G90, Nano-focus Ray Inc., Jeonju, Korea) was used to scan the tube-phantom. Diluted iodine was used as a contrast agent in the experiment. Iodine was injected manually into the phantom in three steps, so that the tubes can be filled one by one. We scanned the tube phantom at each step as described in the following section.

We performed this experiment bearing in mind a practical solution for industrial applications such as frequently visualizing the cross-sectional view of fuel rod assemblies, observing the void fraction and density distribution in a flow for safety analysis in nuclear power plants, or determining the dynamic liquid fraction for different water inlets and flow rates in a laboratory-packed bed reactor. Of course, we can deploy our method for perfusion studies in brain as well. Core idea of this paper is to introduce a method that can effectively implement sparse-view CT imaging in the aforementioned applications, subject to prior images.

2.6. Scanning protocol

Two scanning protocols were used for experimental data acquisition with the micro-CT system. We name them a full scan protocol and a super-sparse scan protocol. In both protocols, a circular scan geometry was used. X-ray tube current and voltage used in both protocols were 80 μA and 70 kVp,
Fig. 5. Reconstructed difference images after injecting contrast agent in; (a) one tube, (b) two tubes and (c) three tubes.

respectively. The full scan protocol was designed to take projection data at 360 views on regular interval and the super-sparse scan protocol was designed to take projection data set at only 15 views on regular interval. The super-sparse scan protocol implies that dose delivered to the scanned object using this protocol is roughly 1/24 times of the full scan protocol [13]. Full scan protocol was used to provide the prior image of the empty tube phantom. The super-sparse scan protocol was used for each scan when the diluted iodine contrast agent was injected into the tube phantom in three steps. In addition, the full scan protocol was also used to provide reference images of the tube phantom at each step for comparison purpose.

3. Results

3.1. Simulation study

Figure 4 shows the reconstructed images of the Shepp-Logan phantom. The prior image reconstructed by the TV algorithm from 360 projections is shown in Fig. 4(a), and the difference image reconstructed also by use of the TV algorithm from 15 projections is shown in Fig. 4(b). Changes have been made to three ellipsoidal components of the phantom by shapes and sizes. Note that the difference image may have negative pixel values. In Fig. 4(c), the superimposed image of the difference image on top of the prior image is shown, which is supposed to be the current image of interest. As shown in Fig. 4(c), accurate image of the modified phantom was reconstructed. Modified phantom image reconstructed by the TV algorithm from projections data at only 15 views without using the prior image is also shown in Fig. 4(d) for comparison. Comparing the images in Figs 4(c) and (d), it is noted that the latter image has some highlighted defects, pointed by arrows, like deformed boundaries of the objects or blurring.

3.2. Experimental study

In order to validate the proposed method experimentally, we used the tube phantom to obtain projection data by use of the two projection protocols as described in the method section i.e. full scan protocol and super-sparse scan protocol. Full scan protocol was used for scanning the empty tube phantom to get the prior image projection data. Prior image was reconstructed by use of the TV algorithm as shown in Fig. 6(a). Diluted iodine contrast agent was injected manually in three steps into the tube phantom. In the first step, contrast agent was injected in a way that only one tube was completely filled, while the remaining two were partially filled. In the second step, one more tube, adjacent to the first filled tube was
completely filled with diluted iodine contrast agent. In the last step all the tubes were completely filled with the contrast agent. In each step after injecting the contrast agent, we scanned the tube phantom with the super-sparse scan protocol and subtracted the projection data from the prior image projection data at corresponding angles. After subtraction, the resulting projection data was used for reconstructing the difference image by use of the TV algorithm. Difference images obtained after each step of injecting the contrast agent are shown in Fig. 5. It is clearly observed that the changes in the difference images were relatively small as shown by the Fig. 5. The modified images were obtained by superimposing the difference images on the prior image as shown in Fig. 6.

We also scanned the tube phantom using the full scan protocol at each step of contrast agent injection to obtain the reference images as shown in Fig. 7. These images were reconstructed by use of the TV algorithm. The results obtained by the proposed method are in a good agreement with the reference images. Horizontal mid-line profiles of the tube phantom images at each step are plotted in Fig. 8 respectively. Each plot consists of the line profiles of the prior, difference, and the superimposed images. The profiles show that the difference images are accurately reconstructed to fill the empty tube regions with minimal modifications to the other existing regions of the prior image. We additionally plotted the line profiles of the reconstructed images from the full scan data in solid lines in Fig. 9. A good agreement between the superimposed images and the reference images is found.

For comparison, we also reconstructed the tube phantom images with the super-sparse scan protocol (i.e., from only 15 views) without using the prior data, and the reconstructed image of which three tubes are filled is shown in Fig. 10. Compared to Fig. 6(d), it is clearly observed that the image reconstructed without using the prior data does not entail the detailed structures of the phantom and has similar image defects as illustrated in the case of Shepp-Logan phantom previously shown in Fig. 4(d).
### Table 1
UQI values of the reconstructed images of a completely filled tube phantom

<table>
<thead>
<tr>
<th>Method</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Without using prior image</td>
<td>0.630</td>
</tr>
<tr>
<td>2 PICCS (alpha = 0.4)</td>
<td>0.922</td>
</tr>
<tr>
<td>3 PICCS (alpha = 0.8)</td>
<td>0.938</td>
</tr>
<tr>
<td>4 PICCS (alpha = 1.0)</td>
<td>0.936</td>
</tr>
<tr>
<td>5 Proposed method</td>
<td>0.965</td>
</tr>
</tbody>
</table>

#### 3.3. PICCS study

A comparison study between the proposed method and the PICCS was also performed. Reconstructed image of a filled tube phantom by use of the proposed method is shown as a reference image in Fig. 11(a). PICCS results are highly dependent on α value. Reconstructed images by use of PICCS at different α values of 1.0, 0.8 and 0.4 are shown as in Figs 11(b)–(d), respectively.

In addition to the visual comparison, a quantitative evaluation of the reconstructed images was also performed. We used a universal quality index (UQI) to measure a degree of similarity between the reference and target image [17]. We used Fig. 7 (c) as a reference image. UQI value ranges from 0 to 1. The closer to 1 the UQI value is, the more similar to the reference image the corresponding image is. The UQI values are summarized in Table 1. The results show that the proposed method produces images of higher UQI value than others. It is also observed that PICCS with higher alpha value produces images of higher UQI.

#### 4. Discussion

We would like to address how the proposed method can effectively reduce the number of projections for image reconstruction by utilizing the prior image of the object. Note that the TV algorithm seeks a solution which satisfies the data fidelity condition and minimizes the image total-variation. A sparse-view CT image reconstruction may be interpreted as solving a system of linear equations that is underdetermined, and there exist an infinite number of solutions that satisfy the system of equations in general. The optimum solution is taken such that the reconstructed image has the minimum image TV. The smaller the image TV is, the sparser the map of image derivative magnitude becomes. We refer to a sparse map of image derivative magnitude as one whose pixel values are mostly zero.

However, the obtained solution or the designed solution may not always be the one that is desired for the purpose of applications. One can imagine that the designed solution under a super-sparsely sampled situation may not be as good as the solution achieved from a sparsely sampled case. It’s because the number of equations provided may be too few to recover the solutions that are non-zero. In other words, the number of equations that are needed to achieve a desired solution depends on the sparseness of the image to be reconstructed. In the proposed approach, the difference image between the two scans is of interest to reconstruct; and the sparseness of the difference image is stronger than that of an image itself in general. Therefore, one can possibly reduce the number of projections for successful reconstruction of the difference image. Jørgensen et al. [18] found that there is a strong correlation between the sparsity of the image and the required sampling density for compressive sensing. In addition, our PICCS study in this work also implies that the image sparsity affects the reconstructed image quality from super-sparsely sampled projections. The proposed method seeks a solution that minimizes the total-variation of a difference image between two scans, which is supposed to be much sparser than the weighted sum of the current image and the difference image as is used in the PICCS.
It may seem that the proposed method is identical to the PICCS in the limiting case of the weighting factor $\alpha$ to be 1, which minimizes the TV of the difference image only. But the actual implementations of the two methods are different in that the proposed method reconstructs the image from experimentally acquired data of both the prior and the current scanned object in a continuous domain. In contrast, the PICCS reconstructs the current image by minimizing the TV of the difference image from computationally acquired data in part. The PICCS compare the experimentally acquired data of a continuous current object and the computationally acquired data of the discrete prior image of the object. Therefore, a discrepancy between these discrete model and continuous model is thought to affect the image quality in the PICCS.
Prior information in CT has been utilized in other works including image fusion method for low-dose CT reconstruction that uses a low-dose CT sinogram data restoration and image domain advanced edge-preserving filtering [19]. Prior data can also be used to avoid artifacts caused by discrepancies between functional and anatomic boundaries [20]. Geometrical information about the target image can also be used as prior information in CT image reconstruction [21]. Similar approaches to our proposed method exist as well in the context of sparse-view CT. Li et al. [22] proposed a row-action type iterative algorithm, using $L_p$-norm ($p \approx 1.1$) as a cost function which is well suited for reconstructing sparse objects. Here, sparse object means object having small number of non-zero pixels in the image. McKinnon-Bates (MKB) method also uses a similar approach to ours, but it is based on the FDK algorithm and therefore is not successful in using few-view data [23]. Cho et al. [14] developed a TV minimization technique that restricts the data to be locally updated during reconstruction. Their approach, however, requires an additional prior knowledge of the region under change.

There are many applications of CT that can potentially make use of the proposed approach. In medical applications, a patient may receive substantial amount of radiation dose from repeated CT scans [24]. One such example is a brain CT perfusion [25,26]. One may achieve reduction in the radiation dose to the patient for the successively following scans in CT perfusion using the proposed technique. CT has also proved its applicability in non-medical imaging area as well [27–29]. It is a big addition to the non-destructive testing of equipments and of process diagnostics in the industries for safer and more efficient operation and design. For example, CT imaging of boiling water reactor (BWR) test assembly shows high resolution images, and can be used to validate the void fraction measured by computational fluid dynamics (CFD) code under steady state conditions [30]. CT imaging can be used to find density distribution, due to the large range of gray scale available depending upon the number of bits supported by the
system, phase fraction and other flow parameters of the object in steady state or transient conditions [29]. Three-dimensional density distribution in a transient unstable stratified flow can be reconstructed using data at limited angles by the proposed techniques [31]. In addition, complex stationary components installed in the industries and fuel assemblies in the nuclear power plants etc. require a big size of detector array and an isotropic source unit. In such a large system, the scanning time required for obtaining projection data at a number of views (450∼780) can be demanding [32]. The proposed method can provide a fast and efficient way of monitoring the system at regular intervals of survey in those applications.

5. Conclusion

We have successfully demonstrated that a super-sparse-view CT imaging, potentially reducing the radiation dose to the patient and reducing the scanning time and efforts, can be achieved by use of the prior image via reducing the number of projections for image reconstruction. The TV minimization algorithm was used for image reconstruction. From the projection data acquired by a super-sparse scanning protocol, we have reconstructed the modified Shepp-Logan phantom successfully. We also demonstrated the feasibility of the proposed method in an experiment using the diluted iodine contrast agent injected to the tube phantom. In the applications where repeated CT scans are necessary, the proposed method is believed to provide an efficient way of reducing the radiation dose and scanning time and efforts. It would be interesting to extend our study to more practical situations using clinical data in order to exploit various image sparsity levels and allowable degree of changes introduced between the scans for successful image reconstruction.

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