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Simultaneous CT-MRI Reconstruction for Constrained Imaging Geometries using Structural Coupling and Compressive Sensing

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Abstract

Objective—A unified reconstruction framework is presented for simultaneous CT-MRI reconstruction.

Significance—Combined CT-MRI imaging has the potential for improved results in existing preclinical and clinical applications, as well as opening novel research directions for future applications.

Methods—In an ideal CT-MRI scanner, CT and MRI acquisitions would occur simultaneously, and hence would be inherently registered in space and time. Alternatively, separately acquired CT and MRI scans can be fused to simulate an instantaneous acquisition. In this study, structural coupling and compressive sensing techniques are combined to unify CT and MRI reconstructions. A bidirectional image estimation method was proposed to connect images from different modalities. Hence, CT and MRI data serve as prior knowledge to each other for better CT and MRI image reconstruction than what could be achieved with separate reconstruction.

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Results—Our integrated reconstruction methodology is demonstrated with numerical phantom and real-dataset based experiments, and has yielded promising results.

Keywords

Computed Tomography; Magnetic Resonance Imaging; Compressed Sensing

I. Introduction

Tomographic modalities such as computed tomography (CT), magnetic resonance imaging (MRI), single photon emission computed tomography (SPECT), and positron emission tomography (PET) are instrumental for clinical imaging. Each of these modalities has distinct advantages: high temporal and spatial resolution with CT; excellent tissue characterization and non-ionizing radiation with MRI; high sensitivity for molecular imaging with SPECT or PET [1-4]. However, no single modality is sufficient to depict the complex dynamics of mammalian physiology and pathology. Hence, multi-modality hybridization/fusion is necessary for superior structural, functional and molecular imaging [5]. An example of multi-physics hybridization was proposed for x-ray micro-modulated luminescence tomography (XMLT) [6]. As evidenced by the successes of SPECT-CT and PET-CT scanners, modality fusion imaging is clearly effective and synergistic and has had tremendous impact on both experimental discovery and clinical care [7-11]. Other hybrid technologies like PET-MRI and XMLT remain on the horizon with tremendous potential [6, 12].

Recently, omni-tomography was proposed for grand fusion of tomographic imaging modalities, and allows for simultaneous acquisition of complementary datasets [13]. Omni-tomography can be the ultimate form of modality fusion. A simultaneous CT-MRI scanner was proposed, as a special case of omni-tomography, to combine high spatial resolutions of CT with high contrast resolution of MRI [13]. Given the commercial availability of various hybrid modalities (e.g. PET-MRI, SPECT-CT), it is not difficult to envision that the CT-MRI concept could lead to the future omni-tomographic trinity of PET-CT-MRI or SPECT-CT-MRI [14, 15]. The advantage of merging tomographic imaging modalities should go beyond complementary attributes, potentially improves results for any individual modality, and is clinically promising for functional imaging studies and radiation therapy [14, 16].

In this paper, a unified reconstruction framework is constructed for simultaneous and integrated CT-MRI image reconstruction. This study specifically combines structural coupling (SC) and compressive sensing (CS) techniques to unify and potentially improve CT and MRI reconstruction. A bidirectional image estimation method was proposed to connect images from different modalities. Hence, CT and MRI data can serve as prior knowledge to each other to produce better CT and MRI image quality than would be realized with individual reconstruction. The SC method is similar to dictionary learning (DL), yet the former is more efficient and flexible than the latter for modality fusion imaging and content-based image estimation [17, 18]. SC is based on local features and establishes a connection between different modality images via a table of paired image patches.

The remainder of the paper is organized as follows. In the next section, we describe the technical details of a CT-MRI scanner, and present the SC-based CT-MRI image reconstruction approach. In the third section, we evaluate the proposed reconstruction scheme with numerical and real experimental datasets in comparison with conventional MRI and CT reconstruction algorithms. In the final section, we discuss relevant issues and draw conclusions.

II. Materials and Methods

A. CT-MRI Scanner

An ideal CT-MRI scanner would acquire MRI and CT measurements of the subject simultaneously. A top-level design of the first CT-MRI scanner was proposed [19] in which CT and MRI sub-systems are seamlessly integrated for local reconstruction, enabled by the generalized interior tomography principle [20]. The CT components are made quasi-stationary with x-ray sources and detectors distributed face-to-face along a circle to overcome space limitation and electromagnetic interference [21]. Given the geometrical constraints, the number of x-ray sources is limited and represents a “few-view” reconstruction problem. A double donut-shaped pair of magnets is used to define a relatively small homogeneous magnetic field in the gap between the magnets, in combination with open configuration allows room for the CT sub-system.

In the proposed CT-MRI scanner, the CT imaging process is the same as for the current commercial CT systems except that the x-ray sources are fixed during a scan, although they could be rotated between scans if needed. Hence, the CT imaging model can be expressed as

$$\mathbf{M}\mathbf{u}_{CT}=\mathbf{f}, \quad (1)$$

where $\mathbf{u}_{CT}$ describes an object to be imaged in terms of linear attenuation coefficients, $\mathbf{M}$ is a system matrix, and $\mathbf{f}$ is line integral data after preprocessing.

In the MRI sub-system, the imaging model is also similar to the conventional model, expressed as

$$\mathbf{R}\mathbf{F}\mathbf{u}_{MRI}=\mathbf{g}, \quad (2)$$

where $\mathbf{u}_{MRI}$ describes the same object but in terms of MRI parameters related to T1, T2, proton density, and so on. $\mathbf{F}$ denotes the Fourier transform, $\mathbf{R}$ is a sampling mask in the k-space, and $\mathbf{g}$ is data.

In an ideal CT-MRI scanner, CT and MRI data are spatially and temporally registered. Alternatively, separately acquired CT and MRI scans can be fused to simulate a simultaneous acquisition. This CT-MRI duality is the base of our proposed simultaneous CT-MRI image reconstruction strategy.

B. Structural Coupling

Given appropriate spatial and temporal co-registration of CT and MRI images, their features can be physically correlated despite their inherently different imaging characteristics. The physical correlation and image compressibility can be collectively utilized via CS, for example using the PRISM method which was adapted for various applications [13]. However, PRISM and similar CS methods capture correlation as low-rank characteristics which are rather general but not very specific. Other methods in the literature, such as [22], cannot well address the joint image reconstruction problem over imaging modalities. Here we suggest use of structural coupling to reflect local similarity more specifically and more effectively for joint multi-modality image reconstruction.

In Fig. 1(a-b), a human abdomen was imaged by CT and MRI, respectively. The images are different representations of the identical physical object. However, the reconstructed pixel values are not well correlated, as suggested in Fig. 1(c-e). Nevertheless, their structural boundaries are quite consistent, and different human beings share very similar anatomic structures.

The principal concept for utilization of CT-MRI image correlation is to pair their local structures in intrinsic corresponding relations, which is a natural coupling of relevant image features. In this study, the connection between CT and MRI image features is maintained in paired CT-MRI patches [17]. They can be generated from one-to-one corresponding CT and MRI image datasets. Given such a CT-MRI dataset, we can extract on one-to-one corresponding patches.

First, prior CT and MRI images are deformed according to currently reconstructed CT and MRI images. The deformed CT-MRI images are much more close to target CT and MRI images under reconstruction. This step will be further described in the section on simultaneous CT-MRI image reconstruction.

Next, bidirectional CT and MRI image estimations are performed using the proposed SC method. The SC method is inspired by locally linear embedding (LLE) theory [23], in which each data point in a high-dimensional space can be linearly represented in terms of the surrounding data points. Specifically, in the SC method, each patch is treated as a point in a high-dimensional space. Any patch $\mathbf{p}_*$ in given images can be linearly expressed with its

similar patches $\mathbf{p}_{*,i}$. Involved weights $\{w_{*,i}\}$ can be determined by a Gaussian function, similar to those used in the non-local mean filtering:

$$w'_{*,i} = \exp\left(-\|\mathbf{p}_* - \mathbf{p}_{*,i}\|_2^2 / h^2\right) \quad \text{and} \quad w_{*,i} = w'_{*,i} / \sum_i^K w'_{*,i} \quad (3)$$

where h is an empirical value that controls contributions of involved patches, K is the number of surrounding data points.

The fundamental principle of the proposed SC method is based on locally linear embedding theory, and stated as that the corresponded CT image patch $\mathbf{p}_{CT}$ can be linearly

approximated with the associated patches in CT dataset $\mathbf{T}_{CT}$ and the same weighting factors

$\{w_i\}$, formulated as $\mathbf{p}_{CT} \approx \sum_i^K w_i \mathbf{p}_{CT,i}$, $\mathbf{p}_{CT,i} \in \mathbf{T}_{CT}$ and $\mathbf{p}_{CT,i} \neq \mathbf{p}_{CT}$, as that for

$\mathbf{p}_{MRI}$ in MRI dataset $\mathbf{T}_{MRI}$. Thus, with the weights $\{w_{*,i}\}$ and the one-to-one correspondence in extracted patch pairs, CT and MRI images are correlated. To implement bidirectional CT and MRI image estimations, a selection vector β_i is applied to both CT and MRI datasets,

$$\min_{\beta_i} \left\| \mathbf{p}_{MRI} - \sum_i w_i \mathbf{T}_{MRI} \beta_i \right\|_2^2 + \left\| \mathbf{p}_{CT} - \sum_i w_i \mathbf{T}_{CT} \beta_i \right\|_2^2, \quad (4)$$

where w_i equals to the average of CT and MRI weightings calculated according to Eq. (3),

$w_i = \frac{w_{CT,i} + w_{MRI,i}}{2}$, β_i identifies surrounding high-dimensional data points. Thus, CT and MRI patches are linked based on prior CT-MRI datasets by sharing the same selection vector and weights. Given a CT image, its corresponding MRI image can be predicted based on prior CT-MRI patches and representation weights. The same scheme can be also applied on the mapping from MRI image to CT image. Here, the optimization of Eq. (4) is empirically implemented: first, find $10K$ -nearest data points in CT and MRI spaces; then, compute the objective function Eq. (4) with the first step results; and finally, choose CT and MRI patches for the minimum value of Eq. (4).

The proposed SC method utilizes the fact that corresponding CT patch and MRI patch are correlated via $\mathbf{T}_{CT-MRI}$ in terms of patch pairs. Although this principle is heuristic at this stage, it has been demonstrated to be valid in a large number of random tests in our preliminary studies (not all included in this paper). An example of the random tests is

demonstrated in Fig. 2, where given an MRI patch $\mathbf{p}_{MRI}$ the corresponding CT patch $\mathbf{p}_{CT}^{est}$ can be estimated using a pre-trained image pair table $\mathbf{T}_{CT-MRI}$ and the resultant $\mathbf{p}_{CT}^{est}$ is very close to the true CT patch $\mathbf{p}_{CT}^{true}$. Fig. 3 shows the estimation results using the proposed SC method from given MRI images. The ground truth CT images and input MRI images are in the first and second columns respectively.

It should be noted that weighting factors $\{w_i\}$ defined in Eq. (3) (and used in Eq. (4)) are not the same results as that obtained by classic LLE theory. The advantage of our scheme is that it measures weight by the Euclidean distance from the reference patch $\mathbf{p}_{MRI}$, and guarantees that $\{w_i\}$ is positive and in a proper range. In our proposed CT-MRI reconstruction, Eq. (4) plays a key role in bidirectional image estimation by sharing the same selection vector β_i and $\{w_i\}$ determined from both MRI and CT sides.

C. Simultaneous CT-MRI Image Reconstruction

CT reconstruction and MRI reconstruction are two well-established research domains, both remain very active [24, 25]. Recently, CS has become popular and been proven effective for most tomographic modalities [26, 27]. CS theory seeks a “sparse” solution for an underdetermined linear system. Total variation (TV) is a widely-used sparsifying

transformation for CS-based CT and MRI reconstruction [28, 29]. The TV-based CT and MRI reconstruction algorithms are respectively written as

$$\min_{\mathbf{u}_{CT}} \|\mathbf{u}_{CT}\|_{TV}, \quad \text{s.t. } \mathbf{M}\mathbf{u}_{CT} = \mathbf{f}, \quad (5)$$

and

$$\min_{\mathbf{u}_{MRI}} \|\mathbf{u}_{MRI}\|_{TV}, \quad \text{s.t. } \mathbf{R}\mathbf{F}\mathbf{u}_{MRI} = \mathbf{g}, \quad (6)$$

where $\|\cdot\|_{TV}$ presents the TV transformation.

In simultaneous CT-MRI reconstruction, CT and MRI datasets are assumed to be spatially and temporally registered. Traditionally, these datasets can be separately reconstructed, and then combined. Intuitively, a joint CT-MRI image reconstruction framework should offer significantly better image quality than individual reconstructions because there are substantial correlations and complementary features between CT and MRI images.

There are two steps in the proposed simultaneous CT-MRI reconstruction: patch-based image estimation and guided image reconstruction. They are iteratively and alternatively performed. The image reconstruction is first started with regular CS-based CT and MRI reconstructions as suggested in Eqs. (5-6). Then, in the image estimation step, the reconstructed CT and MRI images are set as the basis to predict their MRI and CT counterparts with the SC method. In the reconstruction step, the estimated CT and MRI results are used to guide CT and MRI reconstructions respectively. Thus, individual CT and MRI reconstructions are linked together to guide the composite reconstruction synergistically.

In the proposed image reconstruction, prior CT-MRI image patches serves as a bridge to connect the two modalities. The SC method performs the mapping between reconstructed CT and MRI images. In the SC method, prior CT and MRI datasets are first deformed according to the given reconstructed CT and MRI images as shown in Fig. 4 [30]. The newly deformed CT-MRI datasets are much more close to target CT and MRI images in reconstruction. Then, corresponding image patches are extracted from the deformed prior CT and MRI datasets. Subsequently, both reconstructed CT and MRI images are decomposed into patches and updated according to the paired image patches that share the same weighting factors $\{w_i\}$ and the same selection vector β_i in the deformed table $\mathbf{T}_{CT-MRI}$. This process is performed by finding the most similar patches and refining intermediate image patches via linear embedding, as described in the Structural Coupling section.

In the guided image reconstruction, estimated CT and MRI images, which are based on previously reconstructed MRI and CT images, are used to regularize their images in each individual modality reconstruction. They are written as

$$\min_{\mathbf{u}_{CT}} (1 - \alpha) \|\mathbf{u}_{CT}\|_{TV} + \alpha \|\mathbf{u}_{CT} - \mathbf{u}_{CT}^{est}\|_{TV}, \quad \text{s.t.} \quad \mathbf{M}\mathbf{u}_{CT} = \mathbf{f}, \quad (7)$$

and

$$\min_{\mathbf{u}_{MRI}} (1 - \alpha) \|\mathbf{u}_{MRI}\|_{TV} + \alpha \|\mathbf{u}_{MRI} - \mathbf{u}_{MRI}^{est}\|_{TV}, \quad \text{s.t.} \quad \mathbf{F}\mathbf{u}_{MRI} = \mathbf{g}, \quad (8)$$

where $\mathbf{u}_{CT}^{est}$ and $\mathbf{u}_{MRI}^{est}$ are estimated images using the SC method according to the corresponding CT and MRI images. Eqs. (7) and (8) are well-posed convex optimization problems and can be effectively solved using the split-Bregman method [17, 31].

Overall, the proposed simultaneous CT-MRI image reconstruction approach can be formulated as follows:

$$\begin{aligned} & \min_{(\mathbf{u}_{CT}, \mathbf{u}_{MRI}, \boldsymbol{\beta})} \|\mathbf{u}_{CT}\|_{TV} + \lambda \|\mathbf{u}_{MRI}\|_{TV} \\ & + \gamma \sum_j \left(\left\| \mathbf{E}_j \mathbf{u}_{MRI} - \sum_i w_i \mathbf{T}_{MRI} \boldsymbol{\beta}_{j,i} \right\|_2^2 + \left\| \mathbf{E}_j \mathbf{u}_{CT} - \sum_i w_i \mathbf{T}_{CT} \boldsymbol{\beta}_{j,i} \right\|_2^2 \right), \\ & \text{s.t.} \quad \mathbf{M}\mathbf{u}_{CT} = \mathbf{f}, \quad \mathbf{R}\mathbf{F}\mathbf{u}_{MRI} = \mathbf{g} \end{aligned} \quad (9)$$

where $\mathbf{E}$ is an operator to extract patches from an image, and $\boldsymbol{\beta}$ determines which patch is selected for linear approximation by assigning appropriate weighting factors $\{w_i\}$. It is underlined that the same weighting vector $\{w_i\}$ and the same selection vector $\boldsymbol{\beta}$ are used for both CT and MRI patches that reflect the physical correlation between the two images in Eq. (9). Table 1 presents the workflow for simultaneous CT-MRI reconstruction.

In practice, SC is implemented using the hashing method to accelerate the patch searching process [17]. In our experiment, the hashing-based SC step is implemented in MATLAB (MathWorks, Massachusetts, USA) and time-consuming. It usually takes about four hours to process a 256×256 image on an Intel Xeon E5645 2.4GHz CPU. Fortunately, the proposed SC method can be easily accelerated using a high-efficiency programming language, such as C++ on a parallel computing framework such as CUDA, since the patch-wise operations are naturally parallel.

III. Experiments and Results

Preliminary numerical simulations were performed with representative CT and MRI datasets to evaluate the feasibility of the proposed simultaneous CT-MRI image reconstruction approach. In the initial top-level design of a simultaneous CT-MRI scanner there was a limited number of x-ray sources in the CT sub-system, and a low background magnetic field in the MRI sub-system. This cost-effective starting point actually poses an interesting challenge to investigate few-view CT and low-resolution MRI coupling using a simultaneous CT-MRI image reconstruction algorithm.

In our pilot studies, CT and MRI datasets were derived from various sources: 1) established numerical phantoms (modified NCAT phantom (mNCAT)) [32], 2) the Visible Human Project (VHP) [33], and 3) *in vivo* multimodality porcine imaging studies. In these experiments, identical samples were sequentially imaged by CT and MRI scanners. In the numerical phantom experiment, the CT and MRI datasets have perfect spatial registration, as shown in Fig. 3(a). In the other two real dataset experiments, the CT and MRI scans were performed sequentially, thus there were small non-rigid movements between their CT and MRI datasets, and their volumes were in different voxel sizes. Hence, a rigid registration and interpolation process was incorporated to align the CT and MRI datasets as shown in Fig. 3. In the VHP experiment (Fig. 3(b)), the MRI dataset was composed of T2-weighted images. In the porcine multimodality imaging study (Fig. 3(c)), dynamic transaxial CT and MRI images were collected. Sequential CT and MR images were acquired at Yale University of the porcine lower extremity of an anesthetized animal in a fixed position, with the full approval of the Institutional Animal Care and Use Committee. The high-resolution cine CT images of the lower extremities were acquired on a 64-slice CT scanner (Discovery VCT, GE Healthcare) following administration of iodinated contrast (Omnipaque™ 350 mgI/ml) to define vascular anatomy. MRI time-of-flight and phase velocity images were acquired on a 1.5 Tesla MR system (Sonata, Siemens) as non-contrast alternative approaches to define vascular anatomy and flow physiology respectively.

To simulate a simultaneous CT-MRI scan, the CT and MRI images in each experiment were re-projected and re-sampled according to appropriate imaging protocols. In the CT sub-system, the number of x-ray sources was set to 10 in mNCAT experiment, and 15 sources were assumed in the VHP and porcine experiments. Without loss of generality only fan-beam geometry was considered. There were 512 channels per detector array for the numerical phantom, and 400 in the VHP and porcine experiments. In the MRI sub-system, the k-space was sampled in a low-frequency area (Fig. 5) due to the low background field utilized in the combined CT-MRI design. Reconstructed images in mNCAT, VHP and porcine experiments comprise 256×256 , 200×200 , 320×320 pixels respectively.

During the off-line process for the proposed simultaneous CT-MRI reconstruction, three tables of paired CT-MRI image patches, $\mathbf{T}_{CT-MRI}^{mNCAT}$, $\mathbf{T}_{CT-MRI}^{VHP}$ and $\mathbf{T}_{CT-MRI}^{porcine}$ were constructed with CT and MRI slices from mNCAT, VHP and porcine datasets, respectively. It should be noted that there is no overlap between the images used for training CT-MRI patch tables and the images tested for simultaneous CT-MRI reconstruction.

For comparison, the conventional TV-based approach was implemented and applied for separate CT and MRI reconstructions. Both the conventional and proposed algorithms were implemented in the split-Bregman framework [31]. Images were reconstructed with competing algorithms and quantitatively compared in terms of the root-mean-square error (RMSE) [34] and the structural similarity (SSIM) index [35]. The RMSE quantifies the difference between the reconstructed image and the ground truth. The SSIM measures similarity between a reconstructed image and the ground truth. The higher the structural similarity between the two images, the closer the SSIM value approaches 1. In each

experiment, RMSE was used to quantify the differences between the reconstructed and ground truth images with varying patch size (p_n) in $\mathbf{T}_{CT-MRI}$ to choose an optimal value.

According to our analysis (Fig. 7(a)) the optimal patch size was 5×5 pixels for the mNCAT experiment. The same approach was applied to the VHP and porcine experiments both of which yielded the optimal patch size 15×15 pixels, as shown in Figs. 11(a) and 14(a) respectively. In each modality-specific reconstruction, the relaxation parameter α is used to balance the regularization effects of TV in an image and TV between images in Eqs. (7) and (8). Fig. 7(b) shows the RMSE results with different α values. The optimized setting of the parameter α is affected by many factors, such as estimation accuracy, measurement noise and so on. Without loss of generality, in our experiment, α was empirically set to $\alpha = 0.5$.

With the well-trained CT-MRI image pair table, the simultaneous CT-MRI reconstruction method was compared with the conventional TV-based method and the residual errors relative to the ground truths were displayed for the mNCAT, VHP, and porcine experiments in Figs. 6, 9 and 12, respectively. Enlarged views of local regions, denoted by a red box in Figs. 9 and 12, were plotted and compared with the ground truth images for VHP and porcine experiments in Figs. 10 and 13, respectively. In Fig. 8, an error analysis on the mNCAT experiment was performed. Registration errors between CT and MRI images were considered, represented by (x, y) in the unit of pixel. Fig. 8(a-b) shows the results for different registration errors. Fig. 8(c-d) presents the results from 3%, 5% and 10% noisy measurements. In the experiments, Gaussian-type noise was added into both of CT and MRI measurements.

According to our results in Fig. 6, Figs. 9-8 and Figs. 12-11, it is clear that there are less intensity fluctuations in the residual errors of images reconstructed with the simultaneous CT-MRI reconstruction method, as compared with conventional TV-based reconstruction methods. The RMSE index quantified results are shown in Fig. 7(c), Fig. 11(b) and Fig. 14(b). The intermediate reconstruction results of proposed method, quantified with RMSE, are plotted with respect to the iteration index k for comparison. The results suggest that the simultaneous CT-MRI reconstruction algorithm has a fast convergence speed: two outer iterations appear optimal in our experiments. In each loop, two optimization problems (Eqs. (6) and (7)) are involved which are started with zero initial guesses and accordingly estimated images. As compared with conventional iterative reconstructions for CT and MRI, the proposed simultaneous reconstruction method needs extra patch searching step and twice iteration overhead.

In Fig. 10 and Fig. 11, local regions in the CT images from the TV-based and simultaneous CT-MRI reconstructions are enlarged and compared with the ground truth images. By utilizing the physical correlation between CT and MRI images, the simultaneous CT-MRI performance is promising even though the view number of the CT sub-system is significantly lower than a conventional CT scan.

Finally, the reconstructions for the mNCAT, VHP, and porcine experiments were quantitatively compared. The results are summarized in Fig. 15. In these three experiments

the simultaneous CT-MRI image reconstruction using the SC and CS framework always provided better reconstructions compared with the individual reconstructions.

IV. Discussions and Conclusion

The integration and synchrony of tomographic imaging modalities provides the opportunity to test a unified reconstruction framework that not only adds complementary image attributes but also generates information synergy to obtain better image quality than that from an individual modality. It is clearly shown in Figs. 6-15 that the proposed simultaneous CT-MRI reconstruction approach is superior to individual TV-based reconstructions. As demonstrated in Fig. 7(b), the primary reason for such improvement in image quality is utilization of physical correlation between CT and MRI images. Our findings suggest that the physical correlation regularizes and enhances the imaging performance of either CT or MRI (assuming accurate co-registration of involved datasets); and the synergy is more significant in challenging cases such as few-view CT and low-field MRI. The CT and MRI image registration error will degrade the CT image quality significantly, but has a less effect on the MRI image quality, as suggested in Fig. 8(a-b).

In our current implementation of simultaneous CT-MRI image reconstruction, TV was used for image sparseness, which is computationally straightforward. It is acknowledged that more advanced sparsifying transformations, such as dictionary learning [36, 37], could yield better image quality. In Table 1, α was used to balance the regularization effects of TV in an image and TV between images in Eqs. (7) and (8), and was empirically set to 0.5 in the experiments. However, the iteratively estimated image should be increasingly closer to the true image, and the distance between the reconstructed and estimated images should gradually decrease. Thus, the parameter α should be adaptively set with respect to the iteration index for better image quality.

In our simultaneous CT-MRI reconstruction, the SC method links CT and MRI image reconstructions based on physical correlations in the form of paired image patches. According to our pilot study, the physical correlation is critical to improve the performance of each individual imaging modality. Thus, the size, amount, and type of these patches are important. If the patch size were too small, there would be insufficient local features for close coupling of different modalities, and the image estimation workflow (Table 2) would be degraded. On the other hand, if the patch size were too large, it would be difficult to approximate a patch accurately via a linear combination of its K-most similar patches. Other important factors are the amount and types of patches that determine whether the K-most similar patches are powerful enough to represent a given patch. However, this does not imply that a larger number of patches is always preferred, since a longer image patch table will dramatically increase computational complexity. There is an interesting phenomenon that the optimal patch size is 5×5 in the mNCAT experiment; however, the best choice for real experimental datasets (VHP and porcine) is 15×15 . This must be caused by the complexity of the resultant image patches from the real datasets due to their feature-rich information. In future studies, we will systematically evaluate the effect of patch size in an application-specific fashion.

In conclusion, we have presented a simultaneous CT-MRI image reconstruction methodology with the SC and CS techniques as the key components, and qualitatively and quantitatively evaluated the resultant images with numerical phantoms, static human data and dynamic *in vivo* multimodality porcine imaging data. Ideally, a simultaneous CT-MRI scanner would give CT and MRI datasets that are spatially and temporally co-registered. Alternatively, separately acquired CT and MRI datasets can be pre-processed and retrospectively registered as inputs to our proposed reconstruction framework. This retrospectively integrated CT-MR reconstruction approach may improve studies acquired sequentially, when individual scans are separately acquired under suboptimal conditions due to technical limitations or patient issues (fast heart rate, unstable medical condition). Our preliminary results have demonstrated that the performance of the proposed CT-MRI reconstruction algorithm is superior to conventional de-coupled CT and MRI reconstructions. It is underlined that the proposed methodology can be generalized to combinations of other two or multiple tomographic modalities, such as SPECT-CT, PET-MRI, optical-MRI, and omni-tomography in general. The proposed synergistic reconstruction strategy and novel fusion of tomographic imaging modalities not only takes advantage of complementary attributes from each modality but also potentially optimizes the results of any individual modality and lead to hybrid imaging that is time-efficient, cost-effective, and more importantly superior in imaging performance for biomedical applications such as dynamic contrast enhancement studies on cancer and cardiovascular diseases.

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Fig. 1. Comparison between CT and MRI images. (a) and (b) are two well-registered CT and MRI images. They are normalized into $[0, 1]$. (c, d) The line profiles along the white lines in (a) and (b) respectively. (e) The joint histogram of (a) and (b).

Fig. 2.

Structural coupling for image estimation. Any given MRI patch $\mathbf{p}_{MRI}$ can be linearly represented with similar patches in $\mathbf{T}_{MRI}$. Then, the corresponding CT patch $\mathbf{p}_{CT}$ can be linearly represented by the corresponding patches in $\mathbf{T}_{CT}$ with the same weighting factors $\{w_i\}$ as used for representing $\mathbf{p}_{MRI}$.

Fig. 3. Datasets for testing CT-MRI reconstruction. The ground truth CT and MRI images in (a) mNCAT, (b) VHP, and (c) porcine experiments are shown in the first two columns respectively. The third column renders the registration results.

Fig. 4.

Examples of CT and MRI datasets deformation. First, the transforms for CT and MRI datasets are produced based on reconstructed CT and MRI images and the prior CT and MRI datasets. Then, the transforms are applied to the CT and MRI datasets respectively, and new CT and MRI images are generated as improved guesses.

Fig. 5.

Low magnetic field measurements in the MRI sub-system. Sampling patterns in the k-space for (a) mNCAT, (b) VHP, and (c) porcine experiments with undersampling rates of 92.5%, 82.7% and 89.0% respectively.

Fig. 6.

Results of the mNCAT simulation. (a) and (b) are CT images using TV-based and simultaneous CT-MRI reconstructions, respectively. (c) and (d) are reconstructed MR images using the TV-based and CT-MRI method, respectively. (e-h) are the corresponding residual errors relative to ground truths for each reconstruction in the first row. (a-d) are displayed in $[0, 1]$, and (e-h) in $[-0.15, 0.15]$.

Fig. 7.

Analysis on the simultaneous CT-MRI reconstruction with respect to patch size ($\sqrt{p_n}$), relaxation parameter (α) and iteration index (k) in the mNCAT experiment. (a) RMSE quantifies the differences between the reconstructed and ground truth images with respect to various patch sizes $\sqrt{p_n}$. (b) RMSE quantifies the differences between the reconstructed and ground truth images with respect to various relaxation parameter values α . (c) RMSE quantifies intermediate results as a function of the iteration index k ($\sqrt{p_n}=5$).

Fig. 8.

Analysis on the simultaneous CT-MRI reconstruction with respect to various registration errors $(\Delta x, \Delta y)$ and noise levels. (a-b) RMSE quantifies the differences between the reconstructed and ground truth images with respect to various registration errors between CT and MRI images. (c-d) RMSE quantifies the differences between the reconstructed and ground truth images at different noise levels.

Fig. 9.

Results of VHP experiment. (a) and (b) are CT images using TV-based and simultaneous CT-MRI reconstructions, respectively. (c) and (d) are reconstructed MR images using the TV-based and CT-MRI method, respectively. (e-h) are the corresponding residual errors relative to ground truths for each reconstruction in the first row. (a-d) are displayed in $[0, 1]$, and (e-h) in $[-0.2, 0.2]$.

Fig. 10. Comparison over local regions in the VHP experiment. Local enlarged views of (a, d) the ground truth images, (b, e) reconstructed images using the TV-based method, and (c, f) reconstructed images using the proposed simultaneous CT-MRI method.

Fig. 11.

Analysis on the simultaneous CT-MRI reconstruction with respect to patch size ($\sqrt{p_n}$) and iteration index in VHP experiment. (a) RMSE quantifies the differences between the reconstructed and ground truth images with respect to various patch sizes $\sqrt{p_n}$. (b) RMSE quantifies intermediate results as a function of the iteration index k ($\sqrt{p_n}=15$).

Fig. 12.

Results in the porcine experiment. (a) and (b) are CT images using TV-based and simultaneous CT-MRI reconstructions, respectively. (c) and (d) are reconstructed MR images using the TV-based and CT-MRI method, respectively. (e-h) are the corresponding residual errors relative to ground truths for each reconstruction in the first row. (a-d) are displayed in $[0, 1]$, and (e-f) in $[-0.3, 0.3]$, (g-h) in $[-0.2, 0.2]$.

Fig. 13.

Comparison of local regions in the porcine experiment. Local enlarged views of (a, d) the ground truth images, (b, e) reconstructed images using the TV-based method, and (c, f) reconstructed images using the proposed simultaneous CT-MRI method (in (a-c), veins – black; arteries – white, which demonstrate an improved definition of small vascular structures).

Fig. 14.

Analysis on the simultaneous CT-MRI reconstruction with respect to patch size ($\sqrt{p_n}$) and iteration index in porcine experiment. (a) RMSE quantifies the differences between the reconstructed and ground truth images with respect to various patch sizes $\sqrt{p_n}$. (b) RMSE quantifies intermediate results as a function of the iteration index k ($\sqrt{p_n}=15$).

Fig. 15. Quantitative summary of the mNCAT, VHP and porcine experiments. (a) RMSE and (b) SSIM quantify the differences between the reconstructed and ground truth images.

Table 1

Workflow for Simultaneous CT-MRI Image Reconstruction

Inputs:	CT projection data $\mathbf{f}$ and MRI k-space data $\mathbf{g}$
Reconstruction:	<ol style="list-style-type: none"> 1. Reconstruct a CT image $\mathbf{u}_{CT}$ from $\mathbf{f}$ by Eq. (5); 2. Reconstruct an MRI image $\mathbf{u}_{MRI}$ from $\mathbf{g}$ by Eq. (6); 3. $k = 0$; 4. Loop until meeting the stop criteria 5. Transform CT-MRI datasets $\mathbf{T}_{CT-MRI}$ by given $\mathbf{u}_{MRI}$ and $\mathbf{u}_{CT}$; 6. Estimate the corresponded CT-MRI image $\mathbf{u}_{CT}^{est}$ & $\mathbf{u}_{MRI}^{est}$ according to $\mathbf{u}_{MRI}$ & $\mathbf{u}_{CT}$ aided by $\mathbf{T}_{CT-MRI}$ using the SC method (Table 2); 7. Reconstruct the CT image with $\mathbf{u}_{CT}^{est}$ and $\mathbf{f}$ by Eq. (7); 8. Reconstruct the MRI image with $\mathbf{u}_{MRI}^{est}$ and $\mathbf{g}$ by Eq. (8); 9. $k = k + 1$; 10. end

Table 2

Workflow for SC-based CT and MRI Image Estimation.

Input:	MRI image $\mathbf{u}_{MRI}$, CT image $\mathbf{u}_{CT}$, the number of similar patches K
Data transformation	According to Fig. 4, deform CT and MRI datasets based on given CT and MRI images.
Estimation:	<ol style="list-style-type: none"> 1. Decompose $\mathbf{u}_{CT}$ into patches $\mathbf{p}_{CT}^j = \mathbf{E}_j \mathbf{u}_{CT}$; 2. Decompose $\mathbf{u}_{MRI}$ into patches $\mathbf{p}_{MRI}^j = \mathbf{E}_j \mathbf{u}_{MRI}$; 3. Optimize Eq. (4) by finding K-best suitable patches $\{\mathbf{p}_{CT,i}^j\}$ and $\{\mathbf{p}_{MRI,i}^j\}$, and their weights $\{w_i\}$ in $\mathbf{T}_{CT}$ and $\mathbf{T}_{MRI}$ to represent $\mathbf{p}_{CT}^j$ and $\mathbf{p}_{MRI}^j$; 4. Estimate CT and MRI image patches with the corresponded CT and MRI image pairs in $\mathbf{T}_{CT-MRI}$ and new weights $\{w_i\}$, $\mathbf{p}_{new, CT}^j \approx \sum_i^K w_i \mathbf{p}_{CT,i}^j$, $\mathbf{p}_{new, MRI}^j \approx \sum_i^K w_i \mathbf{p}_{MRI,i}^j$; 5. Estimate the corresponded CT image with $\mathbf{p}_{new, CT}^j$, $\mathbf{u}_{CT}^{est} = (\sum_j \mathbf{E}_j^T \mathbf{E}_j)^{-1} (\sum_j \mathbf{E}_j^T \mathbf{p}_{new, CT}^j)$. 6. Estimate the corresponded MRI image with $\mathbf{p}_{new, MRI}^j$, $\mathbf{u}_{MRI}^{est} = (\sum_j \mathbf{E}_j^T \mathbf{E}_j)^{-1} (\sum_j \mathbf{E}_j^T \mathbf{p}_{new, MRI}^j)$.