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A Survey on Predicting CT Image from MRI Data through Feature Matching

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Abstract: Magnetic Resonance Imaging (MRI) provides excellent soft-tissue contrast but lacks the quantitative Hounsfield Unit (HU) information that Computed Tomography (CT) provides. Accurate CT data are essential for radiation therapy dose planning, attenuation correction in PET/MR, and surgical navigation. To reduce the need for dual-modality scanning, researchers have developed algorithms to predict CT images directly from MRI. One important direction is feature matching with learned nonlinear local descriptors, where local MRI patterns are encoded into discriminative descriptors, matched to reference datasets, and mapped to CT values through nonlinear transformations. This paper presents a comprehensive literature survey of MRI-to-CT prediction methods with particular emphasis on approaches that leverage learned nonlinear local descriptors for feature matching and pseudo-CT synthesis. The aim is to highlight the strengths, limitations, and clinical potential of these emerging techniques.

***IndexTerms* – MRI, CT, Deep learning**

I. Introduction

Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) are two of the most widely used medical imaging modalities in clinical practice. While MRI provides excellent soft-tissue contrast, CT remains the gold standard for visualizing bone structures and radiotherapy dose planning due to its ability to represent electron density information. However, acquiring both MRI and CT scans for a patient often increases cost, radiation exposure, and scanning time. This has motivated the development of MRI-to-CT synthesis techniques, which aim to generate pseudo-CT (sCT) images directly from MRI data, thereby avoiding the need for additional CT acquisition [1], [2].MRI-only workflows have become increasingly desirable in clinical settings because they eliminate additional radiation exposure from CT scans and simplify patient preparation. However, MRI cannot directly provide electron density information required for dose calculation in radiotherapy or quantitative attenuation correction in PET/MRI. The ability to predict synthetic CT from MRI has therefore become a critical research goal [1].

Traditional approaches to MRI-to-CT prediction include atlas-based registration, patch-based synthesis, and statistical learning models. However, these methods are limited by anatomical variability, computational complexity, and sensitivity to registration errors [3]. Recently, machine learning and manifold learning approaches have been explored to address these limitations by learning nonlinear relationships between MRI and CT modalities [4]. Furthermore, deep learning methods such as convolutional neural networks (CNNs) and generative adversarial networks (GANs) have demonstrated significant potential in capturing local and global structures for robust MRI-to-CT synthesis [5], [6].

Despite these advances, challenges remain in generalizing models across diverse patient populations, anatomical regions, and scanner settings. This has motivated interest in nonlinear feature descriptors and feature-matching strategies that can bridge the modality gap while preserving structural fidelity [7].

II. Problem Statement

Although MRI-to-CT synthesis has been studied extensively, current methods still struggle to achieve clinically reliable results. Atlas-based and patch-based techniques are often limited by registration errors and poor generalization across patients. Statistical and linear feature-based approaches fail to capture the nonlinear, high-dimensional relationship between MRI intensity patterns and CT Hounsfield Units, leading to inaccuracies in bone detail and electron density representation.

Deep learning has improved performance, but challenges remain with data scarcity, computational complexity, and interpretability. Therefore, there is a critical need for approaches that exploit learned nonlinear local descriptors to bridge the modality gap. Such descriptors can model local structural patterns more effectively, enabling robust feature matching and more accurate pseudo-CT generation.

III. Literature Survey

1. The descriptor-based MRI-to-CT prediction was laid by Yang et al. (2018), who published Predicting CT Image from MRI Data through Feature Matching with Learned Nonlinear Local Descriptors [8]. In this pioneering work, MRI image patches were projected into a nonlinear, high-dimensional descriptor space specifically designed to capture modality-invariant characteristics.

These learned descriptors were then used to perform exemplar-based feature matching between MRI and CT datasets. By combining local descriptor matching with regression techniques, Yang's framework was able to estimate CT Hounsfield Units (HU) with higher structural fidelity compared to handcrafted descriptors like SIFT or HOG. This study was the first to demonstrate that nonlinear learned descriptors could effectively bridge the modality gap between MRI and CT, setting the stage for later descriptor-driven and hybrid deep learning approaches.

2. In 2019, Dusmanu et al. introduced D2-Net: A Trainable CNN for Joint Detection and Description of Local Features [9], which presented a CNN-based framework for joint detection and description of local features. While originally developed for computer vision, D2-Net was later adapted in medical imaging for MRI-to-CT tasks, providing dense descriptors that proved more robust for cross-modality alignment than handcrafted descriptors.

3. By 2020, researchers increasingly explored GAN-based methods for MRI-to-CT synthesis [10]. Conditional GANs and their variants were trained to directly map MRI intensities to CT Hounsfield Units. These networks achieved high quantitative accuracy but were heavily dependent on large paired datasets and were sometimes prone to generating hallucinated structures.

4. In 2021,Sun et al. proposed LoFTR: Detector-Free Local Feature Matching with Transformers [11], which leveraged transformers to generate dense correspondences without explicit key point detection. LoFTR's ability to handle low-texture regions made it especially relevant for MRI–CT prediction. In parallel, hybrid approaches began to emerge, combining handcrafted descriptors such as SIFT and HOG with CNN regressors [12]. These models aimed to use descriptors for local structural accuracy while leveraging CNNs for global intensity consistency.

5. By 2022, attention shifted toward clinical validation of synthetic CT prediction methods [13]. Studies evaluated models not only by voxel-wise metrics (MAE, PSNR, SSIM) but also by their performance in clinical endpoints such as radiotherapy dose-volume histograms (DVH) and PET attenuation correction. Descriptor-based approaches proved useful in low-data clinical environments, while deep learning approaches excelled in multi-center, large-cohort studies.

6. In 2023, van Elmpt et al.published *Current and future developments of synthetic computed tomography [14], a comprehensive review highlighting the evolution of MRI-to-CT synthesis. Their work compared descriptor-based pipelines, GAN architectures, and newer deep learning methods, concluding that descriptor-guided models remain valuable due to interpretability and small-data robustness, while GAN-based models dominate benchmark accuracy.

The field saw significant developments in 2024 with two major reviews. Dayarathna et al. presented Deep learning based synthesis of MRI, CT and PET: A Review [15], focusing on deep learning pipelines including transformers and diffusion models. Their review emphasized that learned descriptors like D2-Net and LoFTR could guide deep models to preserve structural fidelity. Similarly, Bahloul et al. published Advancements in synthetic CT generation from MRI: A review of techniques and trends in radiation therapy planning [16], which specifically examined radiotherapy applications. They concluded that the most promising clinical direction lies in hybrid descriptor–deep learning frameworks, where descriptors enforce anatomical accuracy and deep models provide intensity realism.

IV. Architecture

The proposed architecture for MRI-to-CT synthesis follows a structured sequence of processing stages. First, local descriptors are extracted from MRI scans to capture texture, edge information, and fine-grained anatomical detail beyond raw intensity values. These descriptors may include handcrafted or well-established features such as SIFT or HOG, which provide compact yet discriminative representations of local anatomy.Next, the extracted descriptors are projected into a nonlinear, high-dimensional feature space through kernel-based mappings or explicit feature transforms. This step addresses the inability of linear descriptors to capture the complex and nonlinear correspondence between MRI and CT modalities. To further enhance the robustness of this representation, manifold regularization is applied, ensuring that the learned descriptors preserve local anatomical similarity while aligning MRI features with their CT counterparts.Once the nonlinear descriptors are obtained, they are matched against a pre-collected MRI–CT training dataset. Matching is performed within a constrained spatial neighborhood to maintain anatomical consistency and reduce computational overhead. The corresponding pseudo-CT patches are then estimated using k-nearest neighbor regression, which aggregates matched patches by weighting them according to descriptor similarity. Finally, the estimated patches are merged to reconstruct a continuous pseudo-CT image. Post-processing strategies such as patch averaging or intensity correction may be incorporated at this stage to minimize block artifacts and improve structural fidelity. This multi-stage pipeline thus integrates descriptor learning, nonlinear mapping, and feature matching into a cohesive framework for accurate pseudo-CT generation.

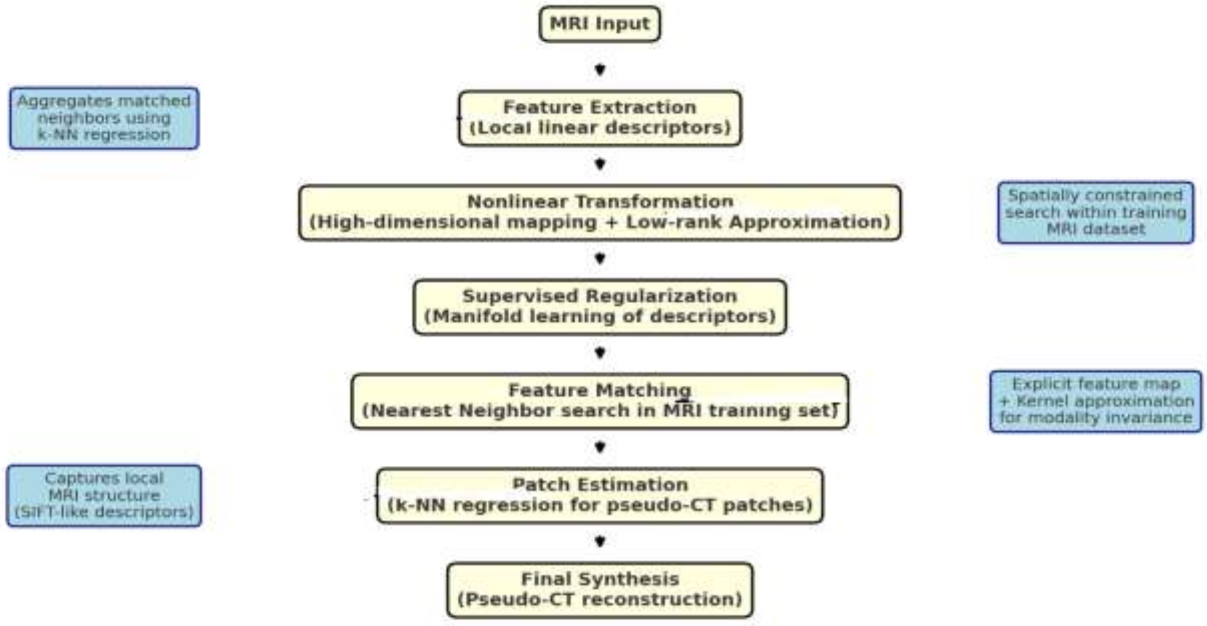

Fig:- Block Architecture of MRI to CT prediction via nonlinear local Descriptors

V. Comparative Analysis and Discussion

The evolution of MRI-to-CT prediction methods demonstrates a progression from classical atlas- and patch-based synthesis to descriptor-driven models and modern deep learning approaches. Atlas-based methods, though interpretable, are hindered by dependence on accurate registration and poor scalability. Patch-based methods improved local prediction but often suffered from boundary inconsistencies and computational inefficiency.

Descriptor-based frameworks introduced a new paradigm by mapping MRI data into nonlinear high-dimensional feature spaces. These methods demonstrated robustness against local structural variation and improved pseudo-CT reconstruction, but their computational demands limited clinical feasibility. Deep learning, particularly convolutional neural networks (CNNs) and generative adversarial networks (GANs), has since become the dominant approach due to its ability to learn complex nonlinear mappings and generate high-quality outputs. Nevertheless, these models remain data-intensive and often act as "black boxes."

Hybrid models that combine descriptor learning with deep architectures are emerging as a promising direction. They attempt to balance interpretability and robustness with the adaptability of end-to-end neural networks. This balance appears essential for achieving clinical-grade performance. Overall, the field is moving toward approaches that prioritize accuracy, generalization across datasets, and clinical usability.

VI. Challenges and Limitations

Despite rapid advances in descriptor-based learning and deep neural models for MRI-to-CT prediction, several challenges remain:

Limited Paired Datasets -: Most frameworks rely on supervised learning using paired MRI–CT scans, which are costly and difficult to obtain in large numbers, especially across different institutions.

Anatomical and Scanner Variability -: Variations in patient anatomy, scanning protocols, and vendor-specific acquisition settings introduce inconsistencies that degrade the generalizability of trained models.

Feature Robustness -: While nonlinear descriptors improve local feature representation, they may still fail to capture global contextual information, leading to blurred bone boundaries or loss of fine structural details in predicted sCT.

Validation and Clinical Translation-: Most studies demonstrate promising results on research datasets, but large-scale multi-center validation and clinical trials remain scarce. Without such validation, clinical adoption remains limited.

Future Directions

Future research in MRI-to-CT synthesis should reduce dependence on paired datasets through self-supervised learning, while exploring advanced architectures such as transformers and diffusion models for improved accuracy. Hybrid descriptor–deep learning frameworks and efficient, real-time implementations will be critical for clinical translation

Conclusion

Descriptor-based MRI-to-CT prediction has matured in parallel with the rapid growth of deep learning approaches. Feature matching with learned nonlinear local descriptors remains valuable for its interpretability, robustness in data-scarce settings, and ability to preserve fine anatomical detail. Recent integration of advanced descriptors such as D2-Net and LoFTR has further improved cross-modality feature alignment. The field is now shifting toward hybrid architectures that combine descriptor-driven local accuracy with the global coherence of deep networks. For successful clinical adoption, future efforts must emphasize multi-center validation, dose-aware evaluation, and the incorporation of explainable AI

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