A Survey of Cross-Modality Brain Image Synthesis

Guoyang Xie\textsuperscript{1,2,∗}, Jinbao Wang\textsuperscript{2,∗}, Yawen Huang\textsuperscript{3,∗}, Yefeng Zheng\textsuperscript{3}, Feng Zheng\textsuperscript{2†} and Yaochu Jin\textsuperscript{4,1†}

\textsuperscript{1}NICE Group, University of Surrey, UK
\textsuperscript{2}VIP Lab, Southern University of Science and Technology, China
\textsuperscript{3}Jarvis Lab, Tencent, China
\textsuperscript{4}Faculty of Technology, Bielefeld University, Germany

\{guoyang.xie, yaochu.jin\}@surrey.ac.uk,
\{wangjb, zhengf\}@sustech.edu.cn,
\{yawenhuang, yefeng.zheng\}@tencent.com

Abstract

The existence of completely aligned and paired multi-modal neuroimaging data has proved its effectiveness in diagnosis of brain diseases. However, collecting the full set of well-aligned and paired data is expensive or even impractical, since the practical difficulties may include high cost, long time acquisition, image corruption, and privacy issues. A realistic solution is to explore either an unsupervised learning or a semi-supervised learning to synthesize the absent neuroimaging data. In this paper, we tend to approach multi-modality brain image synthesis task from different perspectives, which include the level of the supervision, the range of modality synthesis, and the synthesis-based downstream tasks. Particularly, we provide in-depth analysis of how cross-modality brain image synthesis can improve the performance of different downstream tasks. Finally, we evaluate the challenges and highlight several open challenges and future research directions. All resources are available at https://github.com/M-3LAB/awesome-multimodal-brain-image-synthesis.

1 Introduction

The majority of multicenter neuroimaging datasets [Aljabar et al., 2011; Siegel et al., 2019], are often high-dimensional and heterogeneous. For instance, positron emission tomography (PET) and magnetic resonance imaging (MRI) are the imaging techniques to measure the information of organs for auxiliary diagnosis or monitor treatment. The paired/registered multi-modal data provide more complementary information to investigate certain pathologies or neurodegenerations. However, it is not feasible to acquire a full set of completely paired and aligned multi-modal neuroimaging data since: 1) collecting multi-modal neuroimaging data is very costly, for example, a normal MRI can take more than one thousand dollars in some cities; 2) many medical institutions cannot share their data, since medical data are especially restricted to the local regulations, despite the identifiable information can be removed for protecting the privacy of patients; 3) patients’ motions may result in severe misaligned neuroimaging data; 4) the state-of-the-art deformable registration algorithms still require tens of minutes to hours for processing a pair of scans. As a result, there is a clear need to handle the absent data through a cross-modality synthesis method. Figure 1 covers the synthesis range reviewed in this survey. From the number of published papers, we can easily observe that cross-modality brain synthesis has has attracted more and more attention.

Open Challenges As a recent developing area, researches on multi-modality brain image synthesis is still not systematic. The challenging topics required to be investigated are summarized as follows.

- **Q1:** How to jointly optimize the cross-modality neuroimage synthesis and their downstream tasks with either semi-supervised or unsupervised learning? Previously, image synthesis is generally regarded as a standalone task, which seems to have overlooked one important fact: whether the synthesized results can improve their downstream tasks.
- **Q2:** How to ensure the correctness of the synthesized lesions? Previously, most of the cross-modality im-

---

\textsuperscript{∗}Authors contributed equally.
\textsuperscript{†}Corresponding Author
agence synthesis algorithms pay attention to the whole image quality, which fails to highlight the more important disease-related regions (see description in Fig. 5).

- **Q3:** How to build up an appropriate metric to evaluate the results of cross-modality image synthesis? The existing measurements are evaluated by PSNR and SSIM, which are established on natural images but ignore the inherent properties of neuroimage. The translated medical data with highest PSNR or SSIM may be still blurred or missing important tissue representations which should be correctly highlighted.

- **Q4:** How to utilize the misaligned neuroimaging data for cross-modality image synthesis? In practice, there exists many misaligned neuroimaging data in each vendor (i.e., hospital). The state-of-the-art image registration algorithm takes plenty of time for each misaligned brain image. It requires huge amount of labor work to verify the effect of registration algorithm. It’s questionable whether the strong dependence on registration and fully utilization of misaligned data can be eliminated for cross-modality synthesis.

- **Q5:** How to build up a unified model for cross-modality brain image synthesis? Previously, most of work pay attention to various modality synthesis in MR, CT and PET. However, a simultaneous work for synthesizing varying modality among MR, CT and PET is lacked.

- **Q6:** How to solve the data isolation problems without protecting the patients’ privacy for cross-modality brain image synthesis? The current state-of-the-art brain image synthesis algorithms just consider a centralized training strategy. However, many medical institutions cannot share their data, which is restricted to the privacy legislation.

**Related Reviews and Surveys** Yi et al. [2019] provide a comprehensive review of GAN in medical imaging before 2019, including single-modality synthesis, cross-modality synthesis and the usage of GAN in different downstream tasks, e.g. classification, segmentation, registration. However, there are several constraints: 1) The work in [Yi et al., 2019] was published in 2019, whereas most of the reviewed cross-modality synthesis methods in Yi et al. [Yi et al., 2019] are supervised. In other words, most of synthesis algorithms require fully paired medical data for training. 2) The performance of downstream task by leveraging the synthesized results is lost to review. We think it is of great importance since the fundamental purpose of cross-modality synthesis is to work as an auxiliary procedure for their downstream tasks, e.g., segmentation.

Zhao and Zhao [2020] comprehensively review the state-of-the-art deep learning-based methods applied in brain MRI, including segmentation, registration and diagnosis. This work mentions cross-modality brain synthesis but it does not discuss it in detail. Furthermore, a taxonomy review by [Zhao and Zhao, 2020] is presented, which mainly depends on the task without considering the level of supervision. In addition, it reviews brain MRI-related works, generally ignoring other common imaging ways like CT and PET.

Different from previous surveys, we concentrate on cross-modality brain image synthesis by considering the level of supervision, the range of modality synthesis, and the performances on different downstream tasks. Particularly, we deeply analyze how unsupervised and semi-supervised cross-modality synthesis can largely improve the performance of

| Sub-Taxonomy          | Methods                                                                 |
|-----------------------|-------------------------------------------------------------------------|
| Supervised (Sec. 3.1) | Dictionary learning: [Zeiler et al., 2010] [Huang et al., 2017a] [Huang et al., 2017b] GAN: [Wang et al., 2018] [Siddiquee et al., 2019] [Zhou et al., 2020] [Kwon et al., 2019] [Huang et al., 2019a] [Huang et al., 2019a] [Selvaraju et al., 2019] [Yurt et al., 2021] [Jog et al., 2017] [Lee et al., 2019] |
| Semi-supervised (Sec. 3.2) | [Guo et al., 2021] [Guo et al., 2021] [Shen et al., 2021] [Zhou et al., 2021a] |
| Unsupervised (Sec. 3.3) | [Huang et al., 2020b] [Huang et al., 2020a] [Jiao et al., 2020] [Zeng and Zheng, 2019] [Yang et al., 2021] [Yang et al., 2020] [Tomar et al., 2021] [He et al., 2021] |
| MRI To CT (Sec. 4.1) | Supervised: [Huang et al., 2019b] [Huang et al., 2017a] [Joyce et al., 2017] [Chartias et al., 2018] [Zhou et al., 2020] [Kwon et al., 2019] [Huang et al., 2019a] [Li et al., 2019] [Liu et al., 2021] [Ren et al., 2021] [Chartias et al., 2018] [Chen et al., 2021] [Yurt et al., 2021] [Jog et al., 2017] [Sun et al., 2020] [Pan et al., 2021] [Lee et al., 2019] [Toikkanen et al., 2021] [Siddiquee et al., 2019] Semi-supervised: [Huang et al., 2019b] [Huang et al., 2018] [Hemsley et al., 2020] [Guo et al., 2021] [Shen et al., 2021] Unsupervised: [Huang et al., 2020b] [Yang et al., 2021] [Tomar et al., 2021] [Huang et al., 2020a] [Yu et al., 2021] |
| MRI To PET (Sec. 4.2) | [Nie et al., 2017] [Huo et al., 2019] [Zeng and Zheng, 2019] [Zhou et al., 2021a] [Kläser et al., 2021] |
| PET (Sec. 4.3) | [Wei et al., 2018] [Shin et al., 2020] [Pan et al., 2021] [Hu et al., 2022] |
| Ultrasound to PET (Sec. 4.4) | [Jiao et al., 2020] |
| Segmentation (Sec. 5.1) | [Huo et al., 2019] [Chen et al., 2021] [Yu et al., 2021] [Shen et al., 2021] [Zhou et al., 2021a] |
| Classification (Sec. 5.2) | [Pan et al., 2021] [Shin et al., 2020] [Hu et al., 2020] [Liu et al., 2022] |
| Detection (Sec. 5.3) | [Sun et al., 2020] |
| Diagnosis (Sec. 5.4) | [Pan et al., 2021] |
different downstream tasks. Finally, we analyze the growing trend of unsupervised learning and semi-supervised learning.

**Main Contributions** are summarized as follows:

- To the best of our knowledge, it is the first work to deeply review the cross-modality brain image synthesis task by considering the level of supervision, especially for both unsupervised and semi-supervised cross-modality synthesis.
- We are the first one to provide a comprehensive review on the relationship between cross-modality synthesis with their downstream tasks. Our work aims to motivate the medical GANs to focus on how to make an appropriate cross-modality brain image synthesis to correctly improve their downstream tasks, such as image segmentation, registration and diagnosis.
- The proposed work is the first one to summarize the main issues and potential challenges in cross-modality brain image synthesis, which outlines the underlying research directions for future works.

2 **Timeline**

Figure 2 gives a chronological overview of the cross-modality brain synthesis methods on the basis of the level of supervision, the relevant downstream tasks, and the range of modality synthesis. As far as we know, Huang et al. [2017a], Joyce et al. [2017] and Nie et al. [2017] are the first gradient of works to introduce the cross-modality brain image synthesis into the medical GAN community. Their methods are supervised, i.e., their training data are totally paired. Huang et al. construct a closed loop filter learning strategy to learn the convolutional sparse coding (CSC), which is able to eliminate the requirement of large scale training data. Meanwhile, it is also the first one to undertake super-resolution and multi-modality neuroimaging data in MRI. The authors of Joyce et al. [2017] propose a multi-modal modality invariant latent embedding model for synthesis. The purpose of this method is to utilize the mutual information from multi-modality maximally and fuse them into the generated modality image. Nie et al. [2017] introduce a synthesis method by translating brain MRI data to brain CT data. The authors in [Nie et al., 2017] incorporate the detailed information from brain MRI into GANs model to generate the brain CT data. After that, Huang et al. [2017b] provide a first semi-supervised learning approach for cross-modality brain image synthesis. The work in [Huang et al., 2017b] regards the unpaired data as an auxiliary resources. Huang et al. [2017b] propose a hetero-domain image alignment method to enforce the correspondence for unpaired auxiliary data, which can directly substantiate the benefits of the combination with a few paired data and massive unpaired data. Chartsias et al. [2018] firstly propose a unified generator model for various MRI modalities. Huo et al. [2019] firstly apply an unsupervised learning method to cross-modality brain image synthesis. In other words, the multi-modality training data are unpaired. Specifically, the work in [Huo et al., 2019] adopts CycleGAN [Zhu et al., 2017] to generate the target modality data from source modality data. After that, the authors [Huo et al., 2019] leverage both the synthesis modality data and the source modality data for segmentation. It is also the first one to employ unsupervised learning methods for different downstream tasks. Wei et al. [2018] provide a challenging synthesis approach to synthesize from MRI image to PET image. In specific, Sketcher-Refiner GANs proposed by Wei et al. [2018] decompose the synthesis problem as a sketch-refinement process, in which the sketchers generate the preliminary anatomical and physiological information, and the refiner refines the structure of tissue myelin content. Pan et al. [2021] provide a method to jointly optimize both cross-modality synthesis task and the diagnosis task. The authors in [Pan et al., 2021] design a disease-image-specific network (DSNet) by feeding the features generated from disease-image-specific network into Feature-Consistency GANs (FC-GANs) to generate the target domain neuroimaging data. Since DSNet is closely associated with FC-GANs, the missing target domain data can be synthesized in a diagnosis-oriented manner. Hu et al. [2020] and Shin et al. [2020] are the first ones to utilize the synthesized neuroimaging data to improve the performance of a classification task. Zhou et al. [2021b] are the first one to propose a generator to synthesize an arbitrary modality in PET. Klăser et al. [2021] utilize two modalities data, i.e., CT and MRI, to synthesize PET data. Sun et al. [2020] utilize the synthesized data to deal with a brain lesion detection task. Yu et al. [2021] jointly optimize the synthesis and segmentation.

![Figure 2: The chronological review of multi-modality brain image synthesis.](image-url)
problems by using the unsupervised learning methods. Jiao et al. [2020] synthesize MRI from ultrasound image using a new fusion scheme to utilize various modality from unpaired data. Zeng and Zheng [2019] synthesize CT from MR by using the self-supervised methods.

3 Learning Paradigms

3.1 Supervised Methods

Dictionary Learning Before 2018, most of synthesis algorithms adopt convolutional sparse coding (CSC) filter [Zeiler et al., 2010]. But the major drawback of CSC is to require huge amount of paired data to train. Huang et al. [2017a] and Huang et al. [2017b] employ dual filter training strategy and hetero-domain image alignment to significantly reduce the requirement of huge amount of paired data.

GAN Supervised GANs are still the mainstream for cross-modality neuroimaging data synthesis [Wang et al., 2018; Siddiquee et al., 2019]. Zhou et al. [2020] pay more attention to the layer-wise fusion strategy from multiple input modality data and designs a Mixed Fusion Block (MFB) to combine the latent representation from each source modality. Kwon et al. [2019] apply the alpha-GAN to generate 3D brain MRI from a random vector. Huang et al. [2019a] project multi-modality brain MRI data into one common feature space and utilize the modality invariant information represented in the common feature space to generate the missing target domain image space. After that, the authors in [Huang et al., 2019a] apply gradient-weighted class activate mapping (GradCAM) [Selvaraju et al., 2019] to interpret why the synthesis neuroimaging could be utilized for potential clinical usage. Yurt et al. [2021] utilize multi-modalities neuroimaging data and fuse their features to generate the target domain data. Jog et al. [2017] adopt a multi-scale feature extraction scheme and feed the features to three random forest trees to predict the corresponding area of target modality data. CollaGAN is proposed by [Lee et al., 2019], which utilizes the invariant embedding features from multi-modality data and fuses their information to synthesize the target modality data. Tomar et al. [2020] also leverage the high level tasks to guide the cross-modality image synthesis. The similar idea is also applied in [Zhou et al., 2021a].

3.2 Semi-Supervised Methods

Guo et al. [2021] adopt a supervised method to train a lesion segmentation network. Then, the segmentation network was treated as a teacher to guide the generator by using unpaired training data. Similar with the idea from Guo et al. [2021], Shen et al. [2021] also leverage the high level tasks to guide the cross-modality image synthesis. The similar idea is also applied in [Zhou et al., 2021a].

3.3 Unsupervised Methods

Huang et al. [2020b] and Huang et al. [2020a] make full use of unpaired cross-modality data and project them into a common space. Their architectures are described in Fig. 3. The attributed features from the common space bring great helpful to synthesize the missing target modality data. Yu et al. [2021] provide a similar work with the method shown in [Huang et al., 2020b; Huang et al., 2020a]. However, the authors pay more attention to the mouse brain dataset. Jiao et al. [2020] also extract the feature and map them into the common space from different modalities. Moreover, the author in [Jiao et al., 2020] design a new cross-modal attention module for fusion and propagation. Zeng and Zheng [2019] use two models, in which one is the 3D generator network and the other is the 2D discriminator. The authors utilize the result from the 2D discriminator treated as a weak label to supervise the 3D generator, such that the output of the generator can be more close to the output of CT. Yang et al. [Yang et al., 2021] design a uniformed generator for MRI synthesis. The method is also similar with [Huang et al., 2020b; Huang et al., 2020a], which mainly depends on the common feature space. Yang et al. [2020] also borrow the concept of common feature space and design a module to make the feature be more closer from various modalities. Tomar et al. [2021] develop a learnable self-attentive spatial normalization with GAN, which can greatly improve the generator’s performance. He et al. [2021] treat the synthesis problem as the domain generalization problem. The performance of the generator on the unseen target modality cannot be guaranteed due to the domain shift problems.

4 The Range of Modality Synthesis

Since most of work reviewed in this paper are the different modalities of MRI to MRI, we do not give them in more detail. The related references are summarized in Table 1.

4.1 MRI To CT

Computed tomography (CT) is of great importance for different clinical applications, such as PET attenuation correction and radiotherapy treatment planning. However, the patients need to be exposed in radiation during CT acquisition, which may cause side effect. But MRI is much safer than CT. There is a clear need to synthesize CT [Nie et al., 2017; Huo et al., 2019; Zeng and Zheng, 2019; Zhou et al., 2021a] from MRI. Kläser et al. [2021] construct two networks. The role of the first network is to generate CT (pseudo CT) from MRI. The role of the second network is to generate PET from pseudo CT. The total training process can be divided into two parts. The first part is to make pseudo CT be more consistent with the real CT, and the second part is to make the generated PET be more consistent with the real PET.

4.2 MRI To PET

Positron emission tomography (PET) is a very essential measure to measure myelin content changes in-vivo in multiple sclerosis. However, PET imaging is very expensive and invasive due to the injection of a radioactive tracer. In contrast, MRI is much safer since it is not invasive. Therefore, it significantly motivates the researchers to synthesize MRI from PET [Wei et al., 2018]. In addition, PET is also regarded as the gold standard for the diagnosis of Alzheimer’s disease (AD). As previous mentioned, PET can be prohibitive due to the cost and invasive. Shin et al. [2020] propose a conditional GAN to synthesize from MRI to PET where the auxiliary information is from AD diagnosis. Furthermore, Pan et al. [2021] generate MRI from CT and CT from MRI, respectively. Liu et al. [2022] employ a GAN to synthesize PET from MRI and then feed the generated PET and real MRI
into the segmentation task. Hu et al. [2022] employ a bidirectional mapping mechanism to synthesize MR to CT and CT to MR simultaneously.

### 4.3 PET

Unlike previous methods, i.e., one-to-one fixed modality translation, Zhou et al. [2021b] propose a 3D unified cycle-gan (UCAN) to synthesize the arbitrary modality in PET. Wang et al. [2019] propose a 3D auto-encoder to capture various PET modality features into one common space and then utilize the common feature space for synthesize arbitrary PET modalities.

### 4.4 Ultrasound to MRI

Ultrasound is a most common method to detect abnormalities in the fetal brain and growth restriction. However, the quality of ultrasound is easily affected by acoustic windows and occlusions, which mainly come from fetal brain skull. MRI is unaffected by this case and is able to provide more complete spatial details for full anatomy. One major drawback is that the paired data for ultrasound and MRI is extremely difficult to collect. Jiao et al. [2020] employ the self-supervised methods to synthesize MRI from ultrasound images.

### 5 Downstream Tasks

#### 5.1 Segmentation

Huo et al. [2019] directly use the accuracy of the segmented results to evaluate whether the synthesized data is helpful, while lacking to evaluate the quality of the synthesized results by PSNR and SSIM. Chen et al. [2021] pay more attention to the brain MRI of infant. The author in [Chen et al., 2021] incorporate the manual annotations of tissue segmentation maps into the synthesis procedure and make the generated data to be more segmented-oriented. Finally, Chen et al. [2021] prove that the synthesized maps can significantly improve the segmentation accuracy. Yu et al. [2021] jointly optimize the synthesis task and the segmentation task by using an unsupervised learning method. Guo et al. [2021], Shen et al. [2021] and Zhou et al. [2021a] leverage the segmentation task to guide the synthesis task. We notice that the downstream task can also improve the quality of target synthesis domain data.

#### 5.2 Classification

Similar with Pan et al. [2021], Shin et al. [2020] incorporate AD’s information as the auxiliary method to improve the performance of target modality image synthesis. Since the synthesis process is a classification-oriented manner, the synthesized brain image can largely improve the performance of AD’s classification. Hu et al. [2020] design a bidirectional mapping mechanism to preserve the brain structures into the high-dimensional details. The work in [Hu et al., 2020] verifies that the synthesized neuroimaging data can be able to improve the classification accuracy. Liu et al. [2022] jointly optimize the synthesis task and the segmentation task by feeding the features from the generator (encoder and decoder) into the classification network.

#### 5.3 Detection

Sun et al. [2020] treat the synthesis problem as an anomaly detection problem since cross-modality image synthesis can be worked as an auxiliary method to detect the lesion more accurately.

#### 5.4 Diagnosis

Pan et al. [2021] utilize the synthesized neuroimaging data for assisting disease diagnosis. However, this work adopts a supervised learning method by inputting paired multi-modality neuroimaging data, which is difficult to apply to other tasks, since the fully paired data is very difficult to collect.

### 6 Future Research Direction

In Fig. 4, we represent the trend of each learning manner in multi-modality brain image synthesis. We can see that Fig. 4(a) indicates the number of different levels of supervision paper published chronologically. We can easily observe that the number of the unsupervised learning method and semi-supervised learning methods is increasing. The researchers do get more attention to unsupervised learning and semi-supervised learning methods. Fig. 4(b) indicates the number of various downstream tasks with each supervision level method. It can be easily observed that most of the unsupervised learning and semi-supervised methods are jointly optimized with the segmentation task. But the detection, classification, and diagnosis task are ignored by unsupervised learning.
learning and semi-supervised learning methods. Hence, we think that future works should pay more attention to that. Fig. 4(c) presents the modality synthesis range according to levels of supervision. We notice that most of the algorithms would like to conduct cross-modality synthesis for MRI. But PET and MRI to PET have not received enough attention by unsupervised learning and semi-supervised learning algorithm. We expect future works could propose a uniform generator to synthesize an arbitrary modality range among PET, MRI to PET, MRI to CT in unsupervised learning manners or semi-supervised learning manners.

Q1 From all the paper mentioned in this review, we find out that the works for jointly optimizing the synthesis task and their downstream task are very few [Pan et al., 2021; Huo et al., 2019; Shin et al., 2020; Chen et al., 2021; Liu et al., 2022]. The unsupervised learning methods [Yu et al., 2021; Sun et al., 2020; He et al., 2021] and the semi-supervised learning approaches [Shen et al., 2021; Zhou et al., 2021a] start to pay attention to the downstream tasks rather than only focusing on the quality of synthesized results. There are still some down-streams tasks can be applied, such as lesion detection.

Q2 Until now, this question is still unsolved. From our review paper, we predict that the method of [Sun et al., 2020] provides a potential way to solve this question since the lesion diagnosis can be treated as an anomaly detection problem. If we can detect the disease region and use it as the guidance for cross-modality brain image synthesis, the generated output is given in a disease-highlighted and lesion-oriented manner.

Q3 This question is still unsolved. We think it is necessary to build a new metric to evaluate the synthesized quality of images. One of the biggest difference between cross-modality natural images synthesis and brain images synthesis is that the disease region for each modality can be highlighted. However, either PSNR or SSIM is to evaluate the whole image quality without considering the specific region of neuroimaging data.

Q4 Kong et al. [2021] and Xie et al. [2022a] attempt to eliminate the need of registration and make full use of the misaligned neuroimaging data for synthesis. Kong et al. [2021] incorporate the correction loss into CycleGAN [Zhu et al., 2017], while Xie et al. [2022a] regard the misaligned neuroimaging data as a data augmentation of self-supervised learning method and design an affined transform loss to let the discriminator overcoming the overfitting problem. Furthermore, the authors in [Xie et al., 2022a] stimulate the severe misaligned neuroimaging data and find out that their methods perform better in severe misaligned condition. However, both of them [Kong et al., 2021; Xie et al., 2022a] ignore a problem that the data setting of inference process should be included the misaligned data rather than only for the well-aligned data.

Q5 Chartsias et al. [2018] propose a multi-input and multi-output fully convolutional network model to synthesize various modalities of MRI. Similar with Chartsias et al. [2018], Liu et al. [2021] propose a unified conditional disentanglement work to synthesize various modality of MRI. The work in [Liu et al., 2021] adopts a cycle encoder-decoder architecture to extract the invariant features from different modalities. Zhou et al. [2021b] use a cycle-consistant GAN to extract the invariant features from different modalities. Kläser et al. [2021] generate PET modality data by progressively using MRI and pseudo CT data. However, the limitation is that these methods require centralized training method and all training data are paired, which is very difficult to implement in reality. Yang et al. [2021] design a uniform generator for MRI cross-modality synthesis by an unsupervised learning method. However, the uniform generator generated by semi- or self-supervised learning algorithm to synthesize PET from MR and PET from MR are still missing.

Q6 Xie et al. [2022b] is the first one to solve this question. However, the work in [Xie et al., 2022b] do not consider the downstream task with the synthesized neuroimaging data. In this field, there are still lots of spaces to improve.
References

[Aljabar et al., 2011] Paul Aljabar, Robin Wolz, Latha Srivivasan, Serena J. Counsell, Mary A. Rutherford, Anthony David Edwards, Joseph V. Hajnal, and Daniel Rueckert. A combined manifold learning analysis of shape and appearance to characterize neonatal brain development. IEEE Transactions on Medical Imaging, 30:2072–2086, 2011.

[Chartsias et al., 2018] Agisilaos Chartsias, Thomas Joyce, Mario Valerio Gialfrida, and Sotirios A. Tsafaris. Multimodal mr synthesis via modality-invariant latent representation. IEEE Transactions on Medical Imaging, 37:803–814, 2018.

[Chen et al., 2021] Liangjiu Chen, Zhengwang Wu, Dan Hu, Fan Wang, J. Keith Smith, WeiLi Lin, Li Wang, Dinggang Shen, and Gang Li. Abcnet: Adversarial bias correction network for infant brain mr images. Medical image analysis, 72:102133, 2021.

[Guo et al., 2021] Pengfei Guo, Puyang Wang, Rajeev Yasarla, Jinyuan Zhou, Vishal M. Patel, and Shanshan Jiang. Anatomical and molecular mr image synthesis using confidence guided cnns. IEEE Transactions on Medical Imaging, 40:2832–2844, 2021.

[He et al., 2021] Yufan He, Aaron Carass, Lianrui Zuo, Blake E. Dewey, and Jerry L. Prince. Autoencoder-based self-supervised test-time adaptation for medical image analysis. Medical image analysis, 72:102136, 2021.

[Hemsley et al., 2020] Matt Hemsley, Brige P. Chugh, Mark Ruschin, Young Lee, Chia-Lin Tseng, Greg J. Stanisz, and Angus Z. Lau. Deep generative model for synthetic-ct generation with uncertainty predictions. In MICCAI, 2020.

[Hu et al., 2020] Shengye Hu, Yanyan Shen, Shuqiang Wang, and Buiying Lei. Brain mr to pet synthesis via bidirectional generative adversarial network. In MICCAI, 2020.

[Hu et al., 2022] Shengye Hu, Buiying Lei, Shuqiang Wang, Yong Wang, Zhiguang Feng, and Yanyan Shen. Bidirectional mapping generative adversarial networks for brain mr to pet synthesis. IEEE Transactions on Medical Imaging, 41:145–157, 2022.

[Huang et al., 2017a] Yawen Huang, Ling Shao, and Alejandro F. Frangi. Dote: Dual convolutional filter learning for super-resolution and cross-modality synthesis in mri. In MICCAI, 2017.

[Huang et al., 2017b] Yawen Huang, Ling Shao, and Alejandro F. Frangi. Simultaneous super-resolution and cross-modality synthesis of 3d medical images using weakly-supervised joint convolutional sparse coding. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 5787–5796, 2017.

[Huang et al., 2018] Yawen Huang, Ling Shao, and Alejandro F. Frangi. Cross-modality image synthesis via weakly coupled and geometry co-regularized joint dictionary learning. IEEE Transactions on Medical Imaging, 37:815–827, 2018.

[Huang et al., 2019a] Pu Huang, Dengwang Li, Zhicheng Jiao, Dongming Wei, Guoshi Li, Qian Wang, Han Zhang, and Dinggang Shen. Coca-gan: Common-feature-learning-based context-aware generative adversarial network for glioma grading. In MICCAI, 2019.

[Huang et al., 2019b] Yawen Huang, Ling Shao, and Alejandro F. Frangi. Simultaneous super-resolution and cross-modality synthesis in magnetic resonance imaging. In Deep Learning and Convolutional Neural Networks for Medical Imaging and Clinical Informatics, 2019.

[Huang et al., 2020a] Yawen Huang, Feng Zheng, Runmin Cong, Weilin Huang, Matthew R. Scott, and Ling Shao. Mcm-t-gan: Multi-task coherent modality transferable gan for 3d brain image synthesis. IEEE Transactions on Image Processing, 29:8187–8198, 2020.

[Huang et al., 2020b] Yawen Huang, Feng Zheng, Danyang Wang, Junyu Jiang, Xiaojian Wang, and Ling Shao. Super-resolution and inpainting with degraded and upgraded generative adversarial networks. In IJCAI, 2020.

[Huo et al., 2019] Yuankai Huo, Zhoubing Xu, Hyeonsoo Moon, Shuxing Bao, Albert Assad, Tamara K. Moyo, Michael R. Savona, Richard G. Abramson, and Bennett A. Landman. Synseg-net: Synthetic segmentation without target modality ground truth. IEEE Transactions on Medical Imaging, 38:1016–1025, 2019.

[Jiao et al., 2020] Jianbo Jiao, Ana I. L. Namburete, Aris T. Papa-georghiou, and Julia Alison Noble. Self-supervised ultrasound to mri fetal brain image synthesis. IEEE Transactions on Medical Imaging, 39:4413–4424, 2020.

[Jog et al., 2017] Amod Jog, Aaron Carass, Snehashis Roy, Dzung L. Pham, and Jerry L. Prince. Random forest regression for magnetic resonance image synthesis. Medical Image Analysis, 35:475–488, 2017.

[Joyce et al., 2017] Thomas Joyce, Agisilaos Chartsias, and Sotirios A. Tsafaris. Robust multi-modal mr image synthesis. In MICCAI, 2017.

[Kläser et al., 2021] Kerstin Kläser, ThomasVarsavsky, Pavel J. Markiewicz, Tom Kamiel Magda Veraucteren, Alexander Hammers, David Atkinson, K. Thielemans, Brian F. Hutton, Manuel Jorge Cardoso, and Sébastien Ourselin. Imitation learning for improved 3d pet/mr attenuation correction. Medical Image Analysis, 71, 2021.

[Kong et al., 2021] Lingke Kong, Chenyu Lian, Detai Huang, Zhenjiang Li, Yanle Hu, and Qichao Zhou. Breaking the dilemma of medical image-to-image translation. ArXiv, abs/2110.06465, 2021.

[Kwon et al., 2019] Gihyun Kwon, Chihye Han, and Daek-Sik Kim. Generation of 3d brain mri using auto-encoding generative adversarial networks. In MICCAI, 2019.

[Lee et al., 2019] Dongwook Lee, Junyoung Kim, Won-Jin Moon, and J. C. Ye. Collaganc: Collaborative gan for missing image data imputation. 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 2482–2491, 2019.

[Li et al., 2019] Hongwei Li, Johannes C. Paetzold, Anjany Kumar Sekuboyina, Florian Koller, Jianguo Zhang, Jan S. Kirschke, Benedikt Wiestler, and Bjoern H. Menze. Diamondgan: Unified multi-modal generative adversarial networks for mri sequences synthesis. ArXiv, abs/1904.12894, 2019.

[Liu et al., 2021] Xiaofeng Liu, Fangxu Xing, Georges El Fakhri, and Jonghye Woo. A unified conditional disentanglement framework for multimodal brain mr image translation. 2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI), pages 10–14, 2021.

[Liu et al., 2022] Yunbi Liu, Ling Yue, Shifu Xiao, Wei Yang, Dinggang Shen, and Mingxia Liu. Assessing clinical progression from subjective cognitive decline to mild cognitive impairment with incomplete multi-modal neuroimages. Medical image analysis, 75:102266, 2022.

[Nie et al., 2017] Dong Nie, Roger Trullo, Caroline Petitjean, Su Ruan, and Dinggang Shen. Medical image synthesis with context-aware generative adversarial networks. Medical image computing and computer-assisted intervention : MICCAI.
... International Conference on Medical Image Computing and Computer-Assisted Intervention, 10435:417–425, 2017.

[Pan et al., 2021] Yongsheng Pan, Mingxia Liu, Yong Xia, and Dinggang Shen. Disease-image-specific learning for diagnosis-oriented neuroimage synthesis with incomplete multi-modality data. IEEE transactions on pattern analysis and machine intelligence, PP, 2021.

[Ren et al., 2021] Mengwei Ren, Heejong Kim, Neel Dey, and Guido Gerig. Q-space conditioned translation networks for directional synthesis of diffusion weighted images from multi-modal structural mri. In MICCAI, 2021.

[Selvaraju et al., 2019] Ramprasaath R. Selvaraju, Abhishek Das, Ramakrishna Vedantam, Michael Cogswell, Devi Parikh, and Dhruv Batra. Grad-cam: Visual explanations from deep networks via gradient-based localization. International Journal of Computer Vision, 128:336–359, 2019.

[Shen et al., 2021] Liyue Shen, Wentao Zhu, Xiaosong Wang, Lei Xing, John M. Pauly, Baris Turkbey, Stephanie A. Harmon, Thomas Sanford, Sherif Mehralivand, Peter L. Choyke, Bradford J. Wood, and Daguang Xu. Multi-domain image completion for random missing input data. IEEE Transactions on Medical Imaging, 40:1113–1122, 2021.

[Shin et al., 2020] Hoo-Chang Shin, Alvin Ihsani, Ziyue Xu, Swetha Mandava, Sharath Turuvekere Sreenivas, Christopher Forster, Joock Cha, and Alzheimer’s Disease Neuroimaging Initiative. Gandalf: Generative adversarial networks with discriminator-adaptive loss fine-tuning for alzheimer’s disease diagnosis from mri. In MICCAI, 2020.

[Siddiquie et al., 2019] Md Mahfuzur Rahman Siddiquie, Zongwei Zhou, Nima Tajbakhsh, Rubin Feng, Michael B. Gotway, Yoshua Bengio, and Jianming Liang. Learning fixed points in generative adversarial networks: From image-to-image translation to disease detection and localization. 2019 IEEE/CVF International Conference on Computer Vision (ICCV), pages 191–200, 2019.

[Siegel et al., 2019] Rebecca L. Siegel, Kimberly D Miller, and Ahmedin Jemal. Cancer statistics, 2019. CA: A Cancer Journal for Clinicians, 69, 2019.

[Sun et al., 2020] Liyan Sun, Jiexiang Wang, Yue Huang, Xinghao Ding, Hayit Greenspan, and John William Paisley. An adversarial learning approach to medical image synthesis for lesion detection. IEEE Journal of Biomedical and Health Informatics, 24:2303–2314, 2020.

[Toikkana et al., 2021] Miika Toikkana, Doyoung Kwon, and Minho Lee. Resgan: Intracranial hemorrhage segmentation with residuals of synthetic brain ct scans. In MICCAI, 2021.

[Tomar et al., 2021] Devavrat Tomar, Manana Lortkipanidze, Guillaume Vray, Behzad Bozorgtabar, and Jean-Philippe Thiran. Self-attentive spatial adaptive normalization for cross-modality domain adaptation. IEEE Transactions on Medical Imaging, 40:2926–2938, 2021.

[Wang et al., 2018] Yan Wang, Luping Zhou, Lei Wang, Biting Yu, Chen Yu, David S. Lalush, Weili Lin, Xi Wu, Jiliu Zhou, and Dinggang Shen. 3d auto-context-based locality adaptive multimodality gans for pet synthesis. IEEE Transactions on Medical Imaging, 38:1328–1339, 2019.

[Wei et al., 2018] Wen Wei, Emilie Poiron, Benedetta Bodini, Stanley Durrleman, Nicholas Ayache, Bruno Stankoff, and Olivier Colliot. Learning myelin content in multiple sclerosis from multimodal mri through adversarial training. In MICCAI, 2018.

[Xie et al., 2022a] Guoyang Xie, Jinhao Wang, Yawen Huang, Yefeng Zheng, Feng Zheng, and Yaochu Jin. Fedmed-atl: Misaligned unpaired brain image synthesis via affine transform loss. ArXiv, abs/2201.12589, 2022.

[Xie et al., 2022b] Guoyang Xie, Jinhao Wang, Yawen Huang, Yefeng Zheng, Feng Zheng, Jingkuan Song, and Yaochu Jin. Fedmed-gan: Federated multi-modal unsupervised brain image synthesis. ArXiv, abs/2201.08953, 2022.

[Yang et al., 2020] Heran Yang, Jian Sun, Aaron Carass, Can Zhao, Junghoon Lee, Jerry L Prince, and Zongben Xu. Unsupervised mr-to-ct synthesis using structure-constrained cycleGAN. IEEE Transactions on Medical Imaging, 39:4249–4261, 2020.

[Yang et al., 2021] Heran Yang, Jian Sun, Liwei Yang, and Zongben Xu. A unified hyper-gan model for unpaired multi-contrast mr image translation. In MICCAI, 2021.

[Yi et al., 2019] Xin Yi, Ekta Walia, and Paul S. Babyn. Generative adversarial network in medical imaging: A review. Medical image analysis, 58:101552, 2019.

[Yu et al., 2021] Ziqi Yu, Yuting Zhai, Xiaoyang Han, Tingying Peng, and Xiao-Yong Zhang. Mousegan: Gan-based multiple mri modalities synthesis and segmentation for mouse brain structures. In MICCAI, 2021.

[Yurt et al., 2021] Mahmut Yurt, Salman Ul Hassan Dar, Aykut Erdem, Erkut Erdem, and Tolga Çukur. mustgan: Multi-stream generative adversarial networks for mr image synthesis. Medical image analysis, 70:101944, 2021.

[Zeiler et al., 2010] Matthew D. Zeiler, Dilip Krishnan, Graham W. Taylor, and Rob Fergus. Deconvolutional networks. 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pages 2528–2535, 2010.

[Zeng and Zheng, 2019] Guodong Zeng and Guoyan Zheng. Hybrid generative adversarial networks for deep mr to ct synthesis using unpaired data. In MICCAI, 2019.

[Zhao and Zhao, 2020] Xingzhong Zhao and Xing-Ming Zhao. Deep learning of brain magnetic resonance images: A brief review. Methods, 2020.

[Zhao et al., 2020] Tao Zhou, H. Fu, Geng Chen, Jianbing Shen, and Ling Shao. Hi-net: Hybrid-fusion network for multi-modal mr image synthesis. IEEE Transactions on Medical Imaging, 39:2772–2781, 2020.

[Zhao et al., 2021a] Bo Zhou, Chi Liu, and James S. Duncan. Anatomy-constrained contrastive learning for synthetic segmentation without ground-truth. In MICCAI, 2021.

[Zhao et al., 2021b] Bo Zhou, Rui Wang, Ming kai Chen, Adam P. Mecca, Ryan S. O’Dell, Christopher H. van Dyck, Richard E. Carson, James S. Duncan, and Chi Liu. Synthesizing multi-tracer pet images for alzheimer’s disease patients using a 3d unified anatomy-aware cyclic adversarial network. In MICCAI, 2021.

[Zhu et al., 2017] Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A. Efros. Unpaired image-to-image translation using cycle-consistent adversarial networks. 2017 IEEE International Conference on Computer Vision (ICCV), pages 2242–2251, 2017.