Abstract #04245 ISMRM ABSTRACT

Analysis of the Information Contribution of Different Contrast Scans in an MRI Examination aided by Content/style Modeling

Primary: Acquisition & Reconstruction - AI methods) **Secondary:** Analysis Methods - Image Synthesis and Translation) **Oral** · 11 min | AI-Enabled Image Synthesis and Translation · Tuesday, May 12 at 01:40 PM) **Keywords:** MULTI-CONTRAST UNDERSAMPLING MULTI-MODAL MRI CONTENT-STYLE MODELING INFORMATION THEORY

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Impact

Quantification of the information contribution of scans in an MRI exam can assist the operator/radiologist in optimizing exam protocols for high efficiency with minimum information loss. Such optimized exams could reduce strain on the patient, while increasing the hospital's patient-throughput.

Synopsis

Motivation: In MRI exams, different contrast-weighted scans capture the same underlying anatomy, thus having high redundancy. However, precise quantification of this information is needed to improve whole-exam efficiency.

Goals: To quantify the information contribution of the various scans to reduce the total number of measurements in an exam.

Approach: We employ content/style modeling to represent whole exams, utilize information-theoretic metrics to measure scan contribution, and apply it to investigate scan acceleration.

Results: On an in-house brain dataset comprising T1W, T2W, and FLAIR scans, each contrast was found to have contributed equal amount of information to the content of the exam.

Introduction

In an MR exam, multiple scans with different contrast weightings are acquired capturing different aspects of the underlying anatomy. In standard clinical practice, fixed protocols comprising contrasts such as T1W, T2W, FLAIR, etc. are used. Understanding the information contribution of each contrast could inform which scans to include and to what extent a specific scan can be accelerated to achieve optimal efficiency. We address this problem of information quantification within multi-contrast examinations by leveraging content/style modeling[1] and using information-theoretic metrics[2], seeking to answer the following two questions--(a) How much information does each scan contribute to the exam?, and (b) How much acceleration can be performed per scan at a given total exam information loss?

Methods

We formalize the first question as follows--How predictable is a scan given all other scans in an exam? To this end, we construct a leave-one-contrast-out setup where, in an exam comprising N contrasts, the predictability of each contrast from the remaining N-1 contrasts is analyzed. From Liu et al.[2] we adopt the notion of cross-contrast "translatability" defined as the mutual information between a source and a target contrast

$$I(x_t, x_s) := H(x_t) + H(x_s) - H(x_t, x_s),$$

where entropies $H(\cdot)$ are computed using pixel intensity statistics of spatially-aligned contrasts. We generalize this measure to cases with N-1 source contrasts and normalize it by the target contrast's entropy

$$I(x_t, \{x_{s_1}, .., x_{s_{N-1}}\}) := \frac{H(x_t) + H(\{x_{s_1}, .., x_{s_{N-1}}\}) - H(x_t, \{x_{s_1}, .., x_{s_{N-1}}\})}{H(x_t)}.$$

This measure, which we term *Inherent Translatability*, expresses the fraction of a target contrast's information directly predictable from the remaining (source) contrasts.

Content/style modeling[1,3] is a representation learning technique that decomposes two contrast spaces into contrast-independent and contrast-specific components referred to as "content" and "style", respectively. We extend the MUNIT[3] framework to model N-contrast exams, as shown in Figure 1. Using the learned content to represent the underlying anatomical structure measured in an MR exam, we apply it to define *Content-based Translatability*, which expresses the fraction of a target contrast's information encoded in the exam's content estimated from the other N-1 contrasts

$$I(x_t, \hat{c}_{\{s_1,..,s_{N-1}\}}) := \frac{H(x_t) + H(\hat{c}_{\{s_1,..,s_{N-1}\}}) - H(x_t, \hat{c}_{\{s_1,..,s_{N-1}\}})}{H(x_t)},$$

where the content $\hat{c}_{\{s_1,..,s_{N-1}\}}$ is an estimate of the full exam content c^* obtained from N-1 source contrasts. It is computed as voxel-wise mean of the corresponding N-1 content maps as $\hat{c}_{\{s_1,..,s_{N-1}\}} = \frac{1}{N-1}\sum_{i=0}^{N-1} E^c_{s_i}(x_{s_i})$, where E^c_n denotes the content-encoder for the n^{th} contrast.

We address our second question as follows. When accelerating scans by undersampled the k-space, the main concern is that the underlying anatomy must be sufficiently captured. We hence propose to evaluate the loss of information in the exam's content due to the undersampling of each contrast, defining *Exam Content Fidelity* as

$$I(c^*, \hat{c}_{\{s_1,..,s_{N-1}\}\cup\{t_{\text{und}}\}}) := \frac{H(c^*) + H(\hat{c}_{\{s_1,..,s_{N-1}\}\cup\{t_{\text{und}}\}}) - H(c^*, \hat{c}_{\{s_1,..,s_{N-1}\}\cup\{t_{\text{und}}\}})}{H(c^*)},$$

where $c^* = \frac{1}{N}\sum_{n=0}^{N} E_n^c(x_n)$ is the content estimated from all N fully-sampled contrasts, representing the full exam description. Against this reference content we compare the estimate $\hat{c}_{\{s_1,..,s_{N-1}\}\cup\{t_{\text{und}}\}} = \frac{1}{N}(E_t^c(x_t^{\text{und}}) + \sum_{i=0}^{N-1} E_{s_i}^c(x_{s_i}))$ obtained from one undersampled target contrast and N-1 fully-sampled source contrasts. The undersampled scans were reconstructed using the PnP-CoSMo guided reconstruction algorithm[1] using all corresponding N-1 source constrasts as reference.

We validated this concept on an in-house DICOM dataset of patient brains acquired at LUMC. Each exam included 3D T1W TFE, 2D T2W TSE, and 2D FLAIR scans. For training, we used 278 exams from 193 subjects, and 79 exams from 50 subjects as test data.

Results and Discussion

In Figure 2, we first observe that the three contrasts had different inherent predictability, with FLAIR being the most predictable (78% median), followed by T2W (75% median), and finally T1W being the least predictable (70% median) from the corresponding other two contrasts. Second, content-based translatability had roughly similar levels as inherent translatability while being constant across contrasts (as roughly 75% median), suggesting that the learned content is a good representation of MR exams and that all three contrasts contribute equally to it.

Figure 3 plots the influence of acceleration of individual contrasts on the exam content fidelity, and Figure 4 visualizes a set of example content maps. We observe that undersampling FLAIR influenced the exam content the most, followed by T1W, and then T2W. While contributing equally to the exam content, this difference across contrasts upon undersampling may be attributed to a difference in their reconstruction quality. For e.g., while the absence of T1W and T2W affects the exam content equally, a 50% sampled T1W affects the exam content more than a 50% sampled T2W.

Conclusion

Our validation on clinical exams comprising T1W, T2W, and FLAIR scans demonstrated that each scan contributes similar amount of unique information to the exam. Future work will expand this analysis by including more contrasts and larger and more varied datasets with raw k-space data. Furthermore, an information-theoretic analysis focusing on local pathologies is needed for the completeness of our framework.

Acknowledgements

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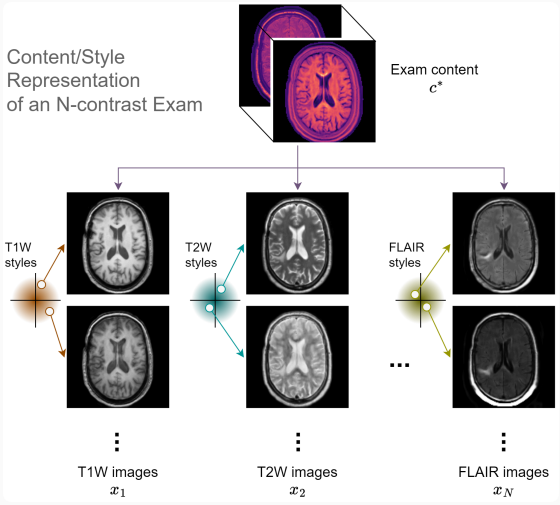
Figures and Tables



Scan for high-resolution version

Figure 1: *Generalized content/style model of N-contrast exams based on MUNIT. Content is shared multi-channel feature map that encodes rich contrast-independent structure, whereas the style is a contrast-specific latent variable encoding variations.*

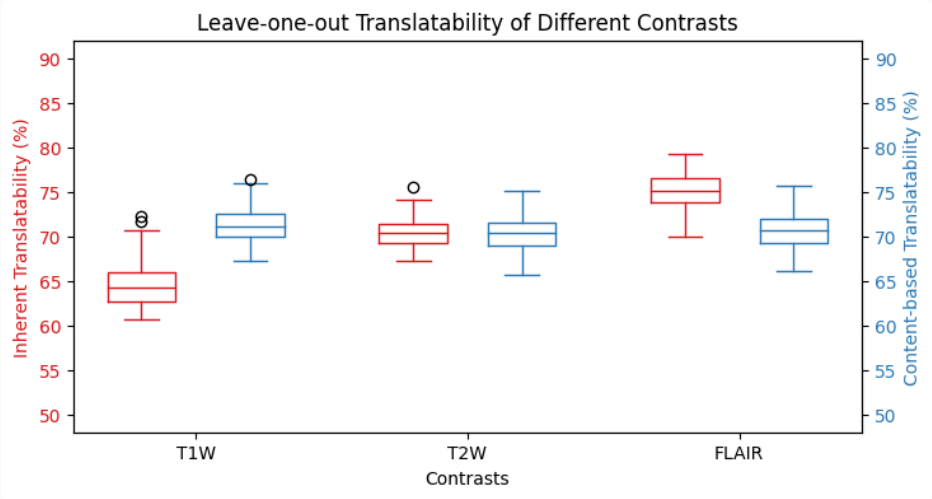


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Figure 2: *Plot showing the inherent translatability (red) and the content-based translatability (blue) of the each of the three contrasts in the exams.*

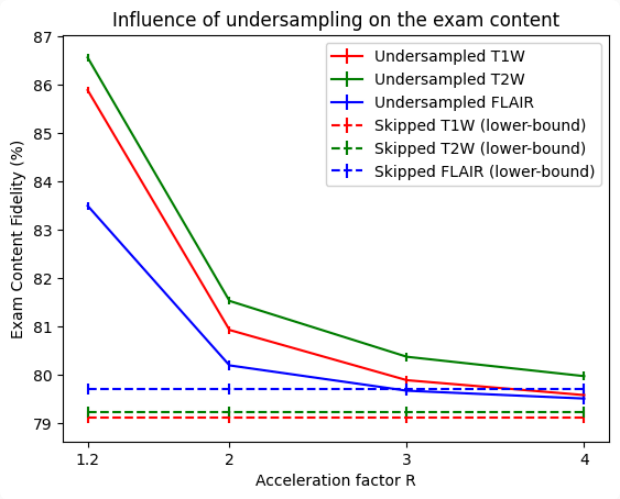

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Figure 3: *Plot showing the influence on the exam content of undersampling a given contrast. Dashed lines show the lower-bound case where a given contrast is entirely skipped and the exam content estimate is computed purely from the remaining two contrasts.*

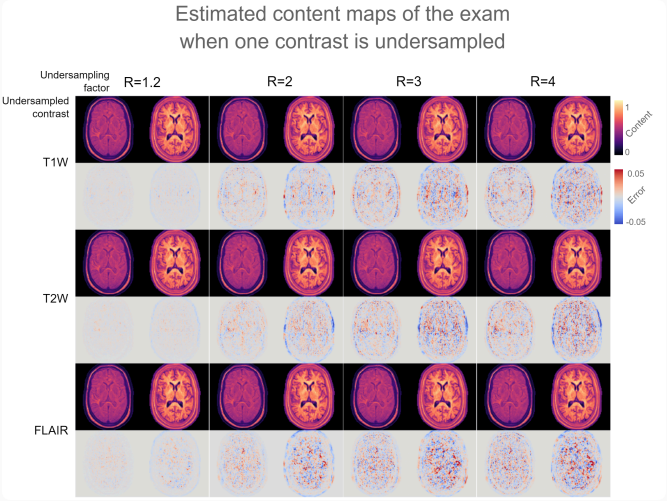

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Figure 4: *Visualization of the estimates of the exam content maps when a given contrast is undersampled.*