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Integration of Probabilistic Atlas and Graph Cuts for Automated Segmentation of Multiple Sclerosis lesions

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Introduction

We propose a framework for automated segmentation of Multiple Sclerosis (MS) lesions from MR brain images. It integrates a priori tissues and MS lesions information into a Graph-Cuts algorithm for improved segmentation results.

Materials and Methods

Pre-processing. The method requires three MR sequences per subject: T1-w, T2-w and FLAIR. MR images are denoised, rigidly registered towards the T1-w image, skull-stripped, bias corrected and normalized [1]. A probabilistic atlas (i.e. CSF, WM, GM and MS lesion probability maps intensity normalized for the four classes, Fig. 1) is registered into the subject space.

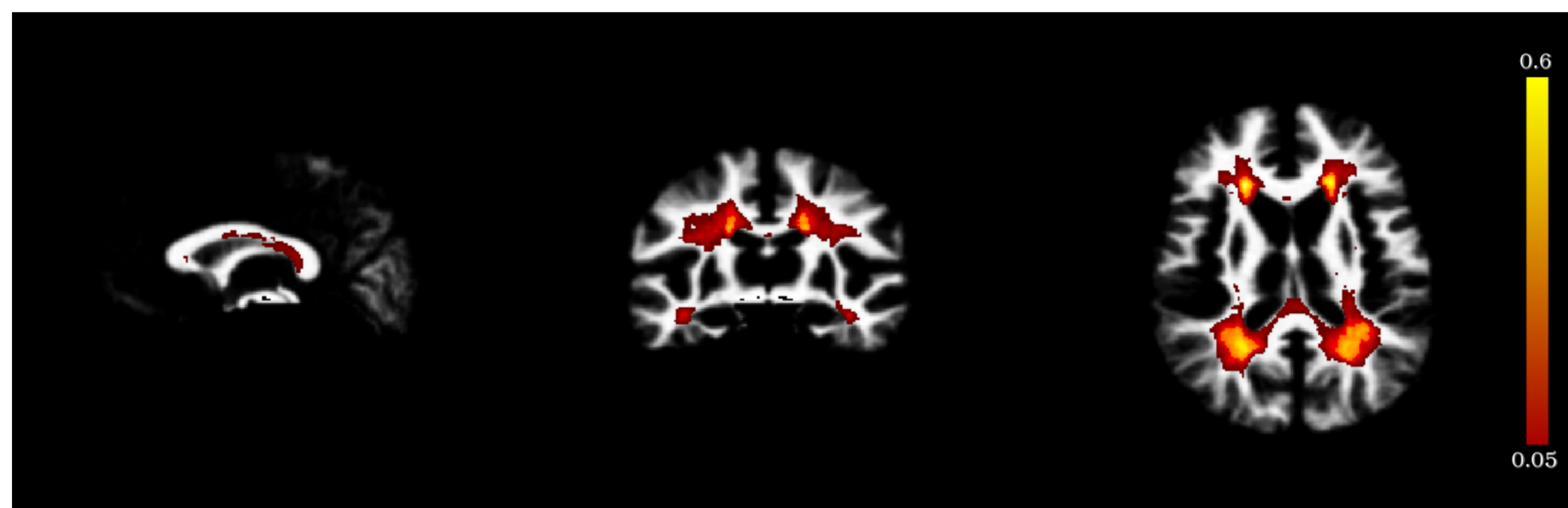


Figure 1: MS lesion probability map overlaid on the WM probability map. MS lesion priors were generated from 89 subjects with manually annotated lesions, with lesion load from 0.1cm^3 to 64cm^3 and a total number of lesions equal to 7927.

Segmentation method. We adopt a Graph-Cuts segmentation approach [1], where the two terminal nodes, *source* and *sink*, respectively represent the MS lesions, or *object class*, and the Normal Appearing Brain Tissues (NABT), or *background class*.

1. Given the set of nodes I and the set of connections N between two nodes $\{i, j\}$, the GC algorithm minimizes an energy function $E(V)$, where V is the *object* segmentation:

$$E(V) = \sum_{\{i,j\} \in N} B_{\{i,j\}} + \alpha \sum_{i \in N} R_i(V_i) \quad (1)$$

The boundary term $B_{\{i,j\}}$ reflects the similarity of neighbour voxels $\{i, j\}$, and the regional term $R_i(\cdot)$ refers to the probability for i to fit into the *object* and *background* models. We compute the boundary weights using the spectral gradient and the *object* and *background* weights as follows.

2. We estimate a 3-class NABT GMM using tissue probability maps initializing a robust EM, which optimizes a trimmed likelihood to be robust to the presence of outliers (e.g. lesions). Then, we evaluate the Mahalanobis distance Z^2 between each voxel i and a tissue class m . Assuming that Z^2 follows a χ^2 distribution, the p-value for a voxel i is obtained as

$$p_{im} = 1 - F_{\chi^2}(Z^2) \quad (2)$$

p_{im} represents the probability that the voxel i does not fit into a class m of the NABT GMM.

3. Voxels that fit into the NABT GMM must have a high *background* weight W_{iB} . We formulate the equation for computing W_{iB} to include both p_{im} and a priori MS lesion information P_{iMS} as

$$W_{iB} = \beta(1 - \min(p_{im})) + (1 - \beta)(1 - P_{iMS}) \quad (3)$$

, where the parameter β (set to 70%) controls the amount of information from the Mahalanobis distance and the prior; $\min(p_{im})$ is the lowest p-value among the m classes for a voxel i .

4. We formulate the *object* weights to include information from the MS lesion prior, the Mahalanobis distance and the hyper-intensities on T2-w and FLAIR images:

$$W_{iO} = \min(P_{iO}, W_{T_2}, W_{FLAIR}) \quad (4)$$

,where

$$P_{iO} = \beta \min(p_{im}) + (1 - \beta) P_{iMS} \quad (5)$$

and W_{T_2}, W_{FLAIR} are fuzzy weights derived from the T2-w and FLAIR hyper-intensities.

Post-processing. A candidate lesion is discarded if one of the following conditions is verified: i) it is not sufficiently located within the WM, ii) it touches the brain mask border, iii) its size is lower than 3mm^3 .

Results

- We evaluated the method on 37 MS subjects (T1-w, T2-w and FLAIR images) [3]. The ground truth was computed using LOP STAPLE on six independent manual segmentations per patient (Fig. 2).
- The average Dice Similarity Coefficient (DSC) was 0.578, the average Positive Predictive Value (PPV) was 0.711. Fig. 3 shows an example of segmentation result (without and with priors).
- The computation time to process a subject on a laptop with an Intel Core i7 CPU 2.40GHz (8 cores) was approximately 10 minutes.

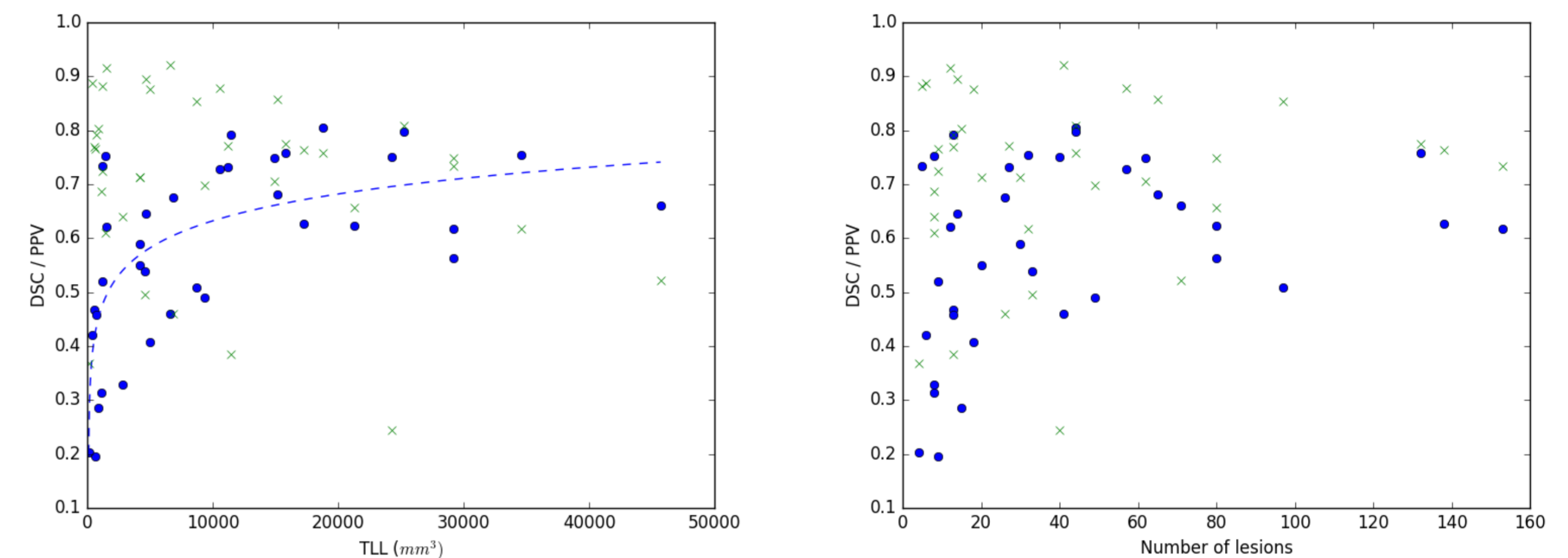


Figure 2: DSC (blue markers), PPV (green markers) and (left) Total Lesion Load (TLL) and (right) number of lesions per patient. Lesion load varied from 0.1cm^3 to 46cm^3 . The number of lesions varied from 4 to 153.

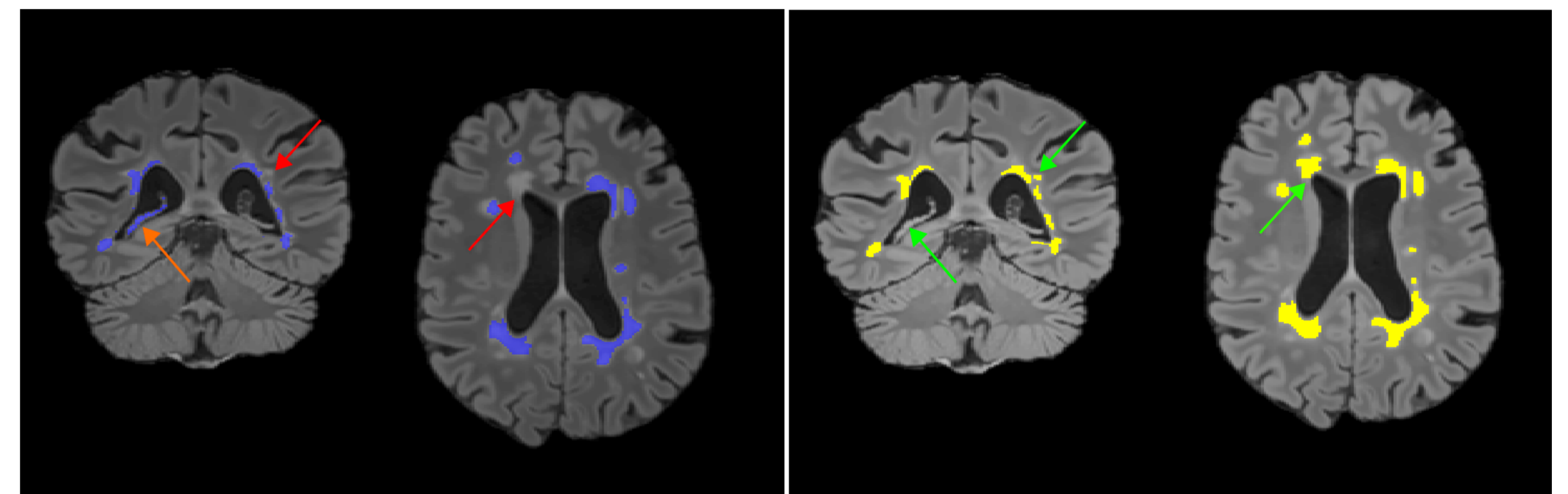


Figure 3: MS lesions segmentation without (left) and with (right) MS lesion priors. Results are overlaid on the FLAIR image. With the use of priors missing lesions (red arrows) can be detected (green arrows) and false positive (orange arrows) can be removed.

Discussion

- Our approach shows generally improved performance compared to a GC approach with no knowledge about MS lesion priors (average DSC=0.480 on the same dataset).
- Three of the MS subjects with low lesion load and low number of lesions obtained a DSC lower than 0.3. This is partially explained by the low experts' agreement for a small lesion load.
- The performance of the proposed method relies on the accuracy of the probabilistic atlas and parameters that must be accurately tuned on a training dataset.
- The method can be easily adapted to be used with different MR sequences (e.g. PD images).

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References

1. Anima-Public: Open source software for image processing from the INRIA VISAGES team.
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