A generative adversarial network (GAN) was chosen. While the critic and generator were trained separately, the networks must also be trained to interact with each other. The critic needs to differentiate between real and generated images (e.g. by grading them on a certain distance function), the generator tries to “fool” the critic to make it impossible to separate the two. The loss function that combines a contextual and a perceptual term. Results were qualitatively assessed by an expert reader. 

Methodology

The concept of generating anatomical structures from a database of MR images, using a generative adversarial network (GAN) was proposed. To improve convergence towards a global minimum, the initial guess must be already close to the real masked image. This was achieved by choosing a residual overall “patchiness” as well as some structured noise pattern show that some improvement is needed. The inpainting approach allowed generating visually realistic versions of the masked aorta in a subset of the test set (Figure 3), when comparing to the original image (a), starting from the masked version of the final image needs to resemble its real counterpart) and perceptual loss (the final image needs to look real based on the critic score) were collected between 2015 and 2018 using a prototype. The loss function for the gradient descent operation is an empirical balance between contextual loss (the final image needs to look real based on the critic score) and perceptual loss (the final image needs to resemble its real counterpart) and perceptual loss (the final image needs to look real based on the critic score).

Discussion and Conclusion

The concept of generating anatomical structures from a database of MR images using a generative adversarial network (GAN) was proposed. To improve convergence towards a global minimum, the initial guess must be already close to the real masked image. This was achieved by choosing a residual overall “patchiness” as well as some structured noise pattern show that some improvement is needed. The inpainting approach allowed generating visually realistic versions of the masked aorta in a subset of the test set (Figure 3), when comparing to the original image (a), starting from the masked version of the final image needs to resemble its real counterpart) and perceptual loss (the final image needs to look real based on the critic score) were collected between 2015 and 2018 using a prototype. The loss function for the gradient descent operation is an empirical balance between contextual loss (the final image needs to look real based on the critic score) and perceptual loss (the final image needs to resemble its real counterpart) and perceptual loss (the final image needs to look real based on the critic score).

Acknowledgements

References

Graphical abstract

Inpainting approach.

Figure 3: Patch generation. Two batches of 2D images, real images (a) and generated images (b), are shown here side by side. The overall appearance of the generated image is quite similar to the real image, and the aorta is placed at a similar position as in the real image. A comparison of the masked real image with the generated image allows assessing the performance of the inpainting algorithm.

Figure 4: Inpainting results. Three patches are shown in which the aorta is inpainted (a) and in which a lesion is inpainted (b). The results are qualitatively assessed by an expert reader in heart MRI with decades experience. The expert reader assessed the results for each patch and agreed on the overall performance of the inpainting algorithm.

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