Multimodal Medical Image Fusion by optimizing learned pixel weights using Structural Similarity index

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***Abstract*— Medical image fusion helps to make finer diagnostic decisions during image guided neurosurgery. In this paper, we propose a novel approach to extract tumor information from MRI volume (3D) and precisely fuse it with intraoperative (IO) thermal and optical images. We feed the rendered MRI volume and images into a trained neural network and select the best weight map by maximising Structural Similarity index (SSIM) of the fused image. Our results convey high visual accuracy in combining information from volumetric as well as image data.**

I. INTRODUCTION

The preoperative modalities e.g. MRI provide structural information like tumor depth/location while IO thermal [1] and optical imaging [2] reveal functional information such as eloquent sites of the exposed cortex. During surgical procedures, neurosurgeons attempt to characterize tissue by visualizing each of these modalities in a single fused image by preserving the inter-correlation between slices of the MRI. We present an approach where we perform volume rendering using Ray casting on the MRI volume to determine precise tumor location and then extract weight maps using a neural network to fuse tumor information of the volume with the IO images.

II. METHOD

The MRI volume V_τ with a fixed depth τ was extracted within the trepanation boundary defined during the surgical resection. Assuming pre-registration of the volume with the thermal (I_{th}) and optical (I_{opt}) images, we define camera matrix as δ and the opacity based rendering operator as $\phi(.)$. The rendered MRI surface can now be termed as $\phi(V_\tau, \delta)$.

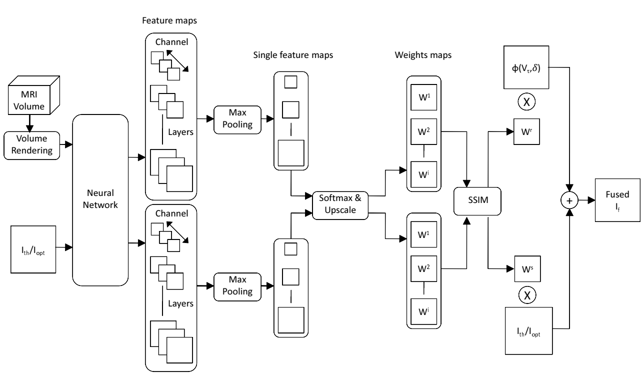

Figure 1. The proposed Multimodal Medical Image Fusion architecture

The MRI surface and the IO modalities were fed to VGG-19 network trained on ImageNet data. The feature channels obtained from the i^{th} layer were compressed using Max Pooling operation to get a single feature map A_n^i for the n^{th} input image at each layer. We then used softmax averaging to calculate the weight maps with $W_n^i = \frac{A_n^i}{\sum_{k=1}^{n} A_k^i}$. The spatial dimension of the weight maps were up-scaled to get weight maps matching the dimension of the input image. We fixed n=2 and i=4 with $1 \leq r, s \leq i$ in our work. We used SSIM [3] and maximised $SSIM(W_1^i * \phi(V_\tau, \delta)) + SSIM(W_2^i * I_{th/opt})$ to determine optimal weight maps W_1^r and W_2^s. SSIM perform luminance, contrast and structure comparisons between the images and therefore, is better suitable than Mean Squared Error (MSE). The fused image is now given by $I_f = W_1^r * \phi(V_\tau, \delta) + W_2^s * I_{th/opt}$.

III. RESULTS

Fig. 2 b) has no visible tumor due to high opacity of $\phi(.)$ while Fig. 2 e) shows ball shaped tumor validated with the groundtruth. The fusion results of Fig. 2 e) with IO images convey that our method provides good visualization of the spatial location of tumor beneath the surface as well as the thermal and visible information of the exposed cortex.

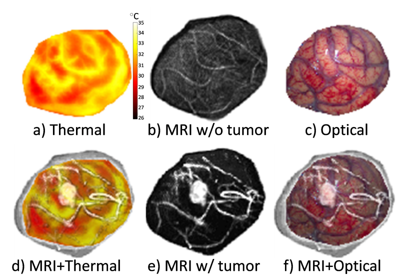

Figure 2. Visual results of the proposed method

IV. DISCUSSION & CONCLUSION

Our approach could be applied for augmented reality based real time tissue characterization during surgeries and might be extended to other preoperative and IO modalities. Though, the volume rendering operation before the fusion strategy has a time constraint, our method has less memory requirements.

REFERENCES

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