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DeepReg: a deep learning toolkit for medical image registration

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Summary

Image fusion is a fundamental task in medical image analysis and computer-assisted intervention. Medical image registration, computational algorithms that align different images together (Hill et al., 2001), has in recent years turned the research attention towards deep learning. Indeed, the representation ability to learn from population data with deep neural networks has opened new possibilities for improving registration generalisability by mitigating difficulties in designing hand-engineered image features and similarity measures for many real-world clinical applications (Fu et al., 2020; Haskins et al., 2020). In addition, its fast inference can substantially accelerate registration execution for time-critical tasks.

DeepReg is a Python package using TensorFlow (Abadi et al., 2015) that implements multiple registration algorithms and a set of predefined *dataset loaders*, supporting both labelled- and unlabelled data. DeepReg also provides command-line tool options that enable basic and advanced functionalities for model training, prediction and image warping. These implementations, together with their documentation, tutorials and demos, aim to simplify workflows for prototyping and developing novel methodology, utilising latest development and accessing quality research advances. DeepReg is unit tested and a set of customised contributor guidelines are provided to facilitate community contributions.

A submission to the MICCAI Educational Challenge has utilised the DeepReg code and demos to explore the link between classical algorithms and deep-learning-based methods (Montana Brown et al., 2020), while a recently published research work investigated temporal changes in prostate cancer imaging, by using a longitudinal registration adapted from the DeepReg code (Yang et al., 2020).

Statement of need

Currently, popular packages focusing on deep learning methods for medical imaging, such as NiftyNet (Gibson et al., 2018) and MONAI (https://monai.io/), do not support image registration. The existing open-sourced registration projects either implement specific published algorithms without automated testing, such as the VoxelMorph (Balakrishnan et al., 2019), or focus on classical methods, such as NiftiReg (Modat et al., 2010), SimpleElastix (Marstal et al., 2016) and AirLab (Sandkühler et al., 2018). Therefore an open-sourced project focusing on image registration with deep learning is much needed for general research and education purposes.

Implementation

DeepReg implements a framework for unsupervised learning (Balakrishnan et al., 2019; Vos et al., 2019), weakly-supervised learning (Hu, Modat, Gibson, Li, et al., 2018; Hu, Modat, Gibson, Ghavami, et al., 2018) and their combinations and variants, e.g. (Hu et al., 2019). Many options are included for major components of these approaches, such as different image- and label dissimilarity functions, transformation models (Ashburner, 2007; Hill et al., 2001; Vercauteren et al., 2009), deformation regularisation (Rueckert et al., 1999) and different neural network architectures (He et al., 2016; Hu, Modat, Gibson, Li, et al., 2018; Simonyan & Zisserman, 2014). Details of the implemented methods are described in the documentation. The provided dataset loaders adopt staged random sampling strategy to ensure unbiased learning from groups, images and labels (Hu, Modat, Gibson, Li, et al., 2018; Yang et al., 2020). These algorithmic components together with the flexible dataset loaders are building blocks of many other registration tasks, such as group-wise registration and morphological template construction (Dalca et al., 2019; Luo & Zhuang, 2020; Siebert & Heinrich, 2020).

DeepReg Demos

In addition to the tutorials and documentation, DeepReg provides a collection of demonstrations, *DeepReg Demos*, using open-accessible data with real-world clinical applications.

Paired images

Many clinical applications for tracking organ motion and other temporal changes require *intra-subject single-modality* image registration. Registering lung CT images for the same patient, acquired at expiratory and inspiratory phases (Hering et al., 2020), is such an example of both unsupervised (without labels) and combined supervision (trained with additional label dissimilarity based on anatomical segmentation). Furthermore, registering prostate MR, acquired before surgery, and intra-operative ultrasound images is an example of weakly-supervised learning for multimodal image registration (Hu, Modat, Gibson, Li, et al., 2018). Another DeepReg Demo illustrates MR-to-ultrasound image registration is to track tissue deformation and brain tumour resection during neurosurgery (Xiao et al., 2017).

Unpaired images

Unpaired images are found in applications such as *single-modality inter-subject* registration. One demo registers different brain MR images from different subjects (Simpson et al., 2019), fundamental to population studies. Two other applications align unpaired inter-subject CT images for lung (Hering et al., 2020) and abdominal organs (Dalca et al., 2020). Additionally, the support for cross-validation in DeepReg has been included in a demo, which registers 3D ultrasound images from different prostate cancer patients.

Grouped images

Unpaired images may also be grouped in applications such as *single-modality intra-subject* registration. In this case, each subject has multiple images acquired, for instance, at two or more time points. For demonstration, multi-sequence cardiac MR images, acquired from myocardial infarction patients (Zhuang et al., 2020), are registered, where multiple images within each subject are considered as grouped images. Prostate longitudinal MR registration is proposed to track the cancer progression during active surveillance programme (Yang et al., 2020). Using segmentation from this application, another demo application illustrates aligning intra-patient prostate gland masks - also an example of feature-based registration based on deep learning.

Conclusion

DeepReg provides a collection of deep learning algorithms and dataset loaders to train image registration networks, which provides a reference of basic functionalities. In its permissible open-source format, DeepReg not only provides a tool for scientific research and higher education, but also welcomes contributions from wider communities.

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