Application of Convolutional Neural Network in Ultrasound Elastography

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Abstract. Ultrasound elastography images elastic properties of biological tissue by using ultrasound imaging technology which can provide significant diagnostic information. Ultrasound scans taken before and after the deformation of a tissue through applied pressure are used to track the displacement of the speckles of the tissue. The strain image of the tissue is obtained from the estimated displacement using least square or gradient method. Some elastography algorithms skip the displacement estimation and estimates the strain profile of the tissue directly from the corresponding ultrasound scans. In both cases, the quality of the strain images can be greatly reduced due to inherent noises such as decorrelation noise, jitter noise etc. Conventional elastography algorithms which primarily involves window-based or pixel-based cross-matching techniques suffer greatly from these types of noise compromising the quality of the estimated strain profile. Advanced machine learning techniques such as convolutional neural network (CNN) offers robust network architectures which provides wide range of depth-of-fields to the input data at different convolutional layers compared to the constant-size window-based or pixel-based conventional methods. Another noteworthy feature of CNN is that previously trained networks can be finetuned with completely new but similar datasets for analogous task; a process known as transfer learning. Incidentally, the task of optical flow estimation in computer vision is very similar to the task of displacement estimation in ultrasound elastography. Recently, CNN architecture FlowNet 2.0 has achieved notable success in optical flow estimation compared to the conventional methods. Naturally, FlowNet 2.0 becomes a prime candidate for robust displacement estimation in ultrasound elastography. At first, we process the ultrasound scans to make them suitable for input to FlowNet 2.0 and used the previously trained weights of FlowNet 2.0 for displacement estimation. The estimated displacement profile by FlowNet 2.0 was, although robust but not fine enough for quality strain image. So we finetuned the coarse displacement estimation by using a global cost function optimizer GLUE to produce fine displacement estimation for calculating strain image. We call our method GLUENet and to the best of our knowledge, this is the first application of CNN in ultrasound elastography. Amazed by the success of GLUENet, our next attempt is to use transfer learning techniques for finetuning the FlowNet 2.0 weights so that it can estimate displacement profile fine enough for calculating quality strain image. We test the performance of the networks by using computer simulated and experimental phantoms, and clinical data.