Learning to Rank with Relative Annotation for Medical Image Analysis

門田, 健明

出版情報：九州大学, 2022, 博士（工学）, 課程博士
バージョン：
権利関係：

（様式 2）

氏　　名　：門田　健明

論 文 名　：Learning to Rank with Relative Annotation for Medical Image Analysis
（医用画像解析のための相対アノテーションを用いたランキング学習）

区　　分　：甲

論　文　内　容　の　要　旨

Deep learning has recently been expected to play a supporting role in disease severity level estimation of medical images. It achieves high performance by training on a large amount of labeled data. Absolute annotation, which represents continuous disease severity to discrete severity levels, is generally assumed to train deep learning for severity estimation. However, absolute annotation is difficult due to ambiguous level judgments. Consequently, attaching absolute annotations, even for medical experts, leads not only to high annotation costs but also to high variability in the judgment. In contrast, relative annotation, which represents which of two images has a higher severity, is expected to be simple and has low variability. This thesis proposes two methods for estimating disease severity by learning to rank with relative annotations. The first method is multi-task learning, which combines learning to rank by relative annotation and regression learning by absolute annotation. This method can substantially reduce the annotation cost by using relative annotations and a small number of absolute annotations. In a severity classification task of ulcerative-colitis endoscopic images, the proposed method achieved higher classification performance (accuracy and F1 score) with 10¥% annotation cost compared to the conventional classification methods only with absolute annotation. The second method is active learning using a Bayesian convolutional neural network (CNN) for determining image pairs to which relative annotations should be attached. This method is an active sample selection based on uncertainty given by the Bayesian CNN. The relative severity level estimation results showed that this method performs better than methods trained by randomly paired samples. The results also showed that this method is robust to class imbalance because it selects minor but important samples during its uncertainty-based selection.