Dilation-Erosion Methods for Radiograph Annotation in Total Knee Replacement

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INTRODUCTION

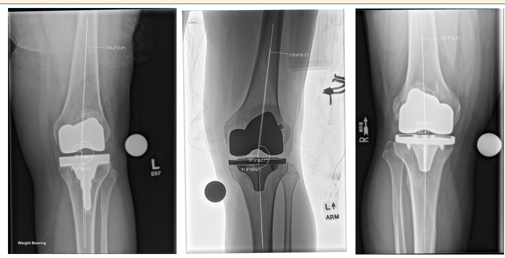

Fig 1. Example of manual placement of markers made by orthopedic clinicians for assessment

- Post-surgical evaluation of TKR relies partially on radiographs of the patient's knee and implant, and the alignment of that implant to the femur and tibia
- Manual placement of markers for assessments are made by orthopedic clinicians
- Automation of this placement is a clear target for learned medical vision systems
- Benefits of automated marker placement: radiograph assessments without expert intervention, possibly for in-the-field point-of-care assessment, or for reducing assessment loads when assessing retrospective studies of large databases.

METHOD

- Simple augmentation is invalid in TKR since the bones have rigid structure and clear obvious orientation, so spatial augmentations will distort patterns and break the meaning of the labels and/or produce invalid radiographs
- We instead propose a Dilation-Erosion label augmentation method, which augments the label by dilating and eroding the label on a cooling schedule
- We used the angular difference between prediction and ground truth as the loss function for our model

$$Loss = 1000 \times Pixel\ Loss + Angular\ Loss$$

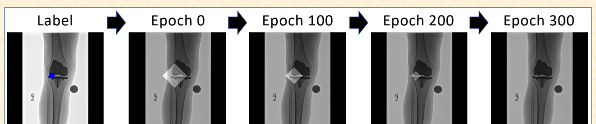

Fig 2. Example of Dilation-Erosion method

$$\tilde{w} = w \times \frac{\text{input image size} - (\text{number of dilated pixels} + \text{number of label pixels})}{\text{number of dilated pixels} + \text{number of label pixels}}$$

1. Image labels are first dilated by a set number of image dilation iterations where dilated labels are allowed to overlap
2. Prediction network is trained using the dilated labels and labels are then eroded over a schedule based on training steps taken
3. As adjusting the size of each label as training progresses, we re-weight the error function, biasing predictions away from degenerate solutions.

RESULT 1 – Label Prediction

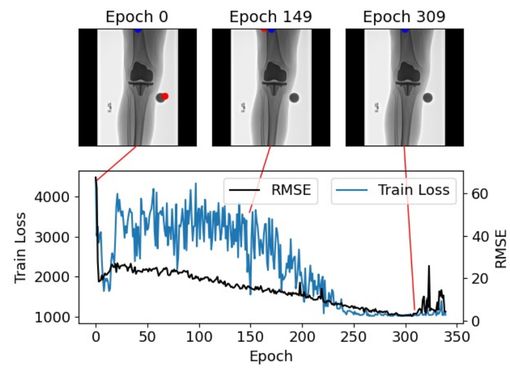

Fig 3. Training loss (left y-axis) and mean RMSE (right y-axis) across epochs with exemplar predicted outputs (red) and ground truth labels (blue) for Epoch 0, 149, and 309

- Extracted the pixel with the highest value in the prediction
- The lowest mean RMSE, distance from label to prediction, or also called as pixel difference, was 2.3 which decreased from 67 at Epoch 0

RESULT 2 – Angle Prediction

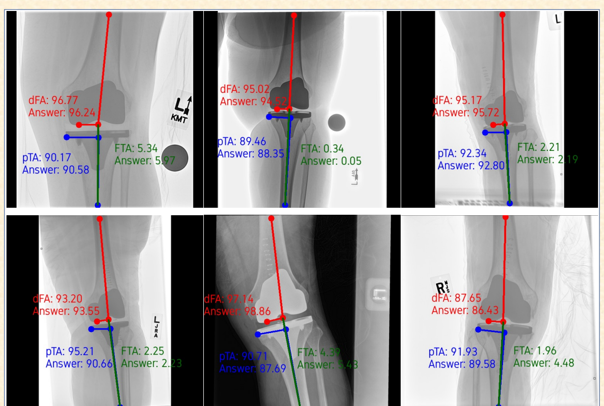

Fig 4. Visualization of angles on validation set

- From the pixel extracted in RESULT 1, we calculated patella-tibia angle(pTA), femur-tibia angle(FTA), and distal femoral angle(dFA)

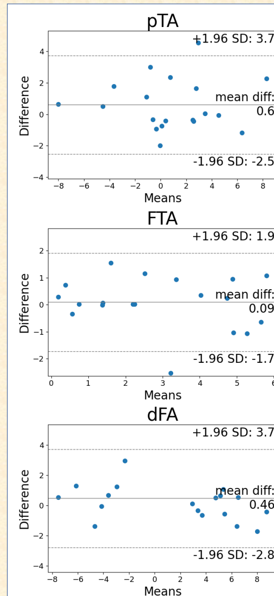

Fig 5. Bland-Altman analysis of three angle predictions

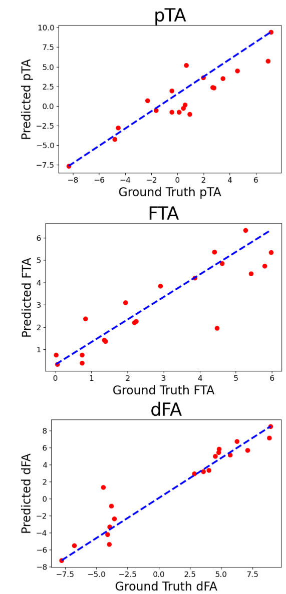

Fig 6. Scatterplot of relationship between ground truth angle and predicted angle

- The lowest mean angular difference between ground truth and prediction was 1.0°, where absolute mean angular difference for each pTA, FTA, dFA was 1.3°, 0.7°, 1.1°

FUTURE WORK

- Expand the dataset and evaluations to include lateral views and annotations, and assess inter-rater reliability to determine the noise ceiling of accuracy

Paper

https://openreview.net/pdf?id=bVC9bi_-t7Y

Github Code

github.com/yehyunsuh/Total-Knee-Replacement-Post-Surgical-Assessment