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Wrist Big ROI Extraction for Bone Age Assessment in Smart Intelligence Systems

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Abstract: Recently, the number of children receiving medical treatment because of precocious puberty has increased. One diagnosis method for detecting precocious puberty is a bone age assessment which evaluates a child's bone age by observing the shape of bones and joints. In this study, we developed a process to extract wrist big Region of Interest (ROI) to help extract 2 assessed bones required for the Tanner-Whitehouse 3 (TW3) assessment. We investigate the test methods and results for the algorithm derived from various tests. Through various methodologies, the wrist big ROI are obtained among which the 13 assessed bones in the wrist required by TW3 are included.

Key words: Wrist big ROI, TW3, bone age assessment, smart intelligence systems, wrist, puberty

INTRODUCTION

Recently, the number of children receiving medical treatment because of precocious puberty has increased. Precocious puberty means having the signs of puberty at the early age of eight or younger in girls and nine or younger in boys. There are various causes of precocious puberty, including obesity, heredity, eating habits, stress, environment and hormones. Precocious puberty affects not only growth in terms of height but it can also, negatively affect study habits or induce other forms of psychological suffering. Especially in the case of girls, the risk of premature menopause, breast cancer, uterine cancer, etc. can become higher. However, in most cases, people miss opportunities for medical diagnosis of precocious puberty. Sometimes, they are not even aware of it.

One diagnosis method for detecting precocious puberty is a bone age assessment which evaluates a child's bone age by observing the shape of bones and joints. The assessment time varies, depending on the skill of the specialist. Furthermore, because each doctor may have a different subjective opinion, the results of the diagnosis may vary. Because of problems such as the complexity of the assessment process, long assessment times and errors caused by subjective opinions, pediatric and radiology specialists have ceaselessly advocated for automatic bone age assessment systems.

Recently, deep learning has become a hot issue in the medical image analysis field (Simonyan and Zisserman, 2014, Ren *et al*., 2017, Litjens *et al*., 2017, CNN., 2018). As the performances of hardware devices have advanced, deep learning studies which did not originally receive much attention because of their long and complex computation requirements have been actively conducted. We are also working on a study that applies deep learning to the Tanner-Whitehouse 3 (TW3) method (Tanner *et al*., 2001, Griffith *et al*., 2007) which assesses bone age via. an X-ray image of the left hand. In this study, we developed a process to extract an image region required for the TW3 assessment. Especially, a large region is extracted, including the 2 bones to be assessed, using a preprocessing technique. We call this big image region as wrist big Regions of Interests (ROIs). The four big ROIs include bones from the wrist, thumb, middle finger and little finger, respectively for TW3. Using the wrist big ROI reduces the risk of confusion because the many bones required for TW3 have similar shapes and names. Thus, by extracting wrist big ROI, we increase the accuracy of the assessed bone extraction. To do this, we have tried various methodologies and have derived a final methodology.

In this study, we describe our preprocessing method which increases the accuracy of the deep learning-based bone age assessment system of the TW3 method. We investigate the test methods and results for the algorithm derived from various tests. The preprocessing methods include various methodologies: image binarization which separates a hand from the background; image rotation which places the assessed bone in the upright position; and extraction of wrist big ROIs containing the assessed bones. Through various methodologies, the wrist big ROI are obtained among which the 2 assessed bones in the wrist required by TW3 are included. In this study, we describe the preprocessing method, used to increase the accuracy of extracting the assessed bones needed for the TW3 method. Especially, we describe the way to extract the wrist big ROI from an original X-ray

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image. The performance of the methodologies included bin our preprocessing method are verified as well.

MATERIALS AND MATHODS

Convex hull and RANSAC: Convex hull refers to a set containing polygon vertices of n points. A typical algorithm for the convex hull is the Graham scan. Suppose there are three arbitrary points, p1-p3. In the case of the outer product value of two vectors is larger than 0, if a line is drawn sequentially from p1-p3, it is turned in the counter-clockwise direction (left) from the position of p2. In the case of the outer product is smaller than 0, it is turned in the clockwise direction (right). In the case of 0, the 3 points are located along the same line. Therefore, a convex hull can be found. This method can be applied when finite points are given. Therefore, for this study, if an outline of the left hand is extracted from an X-ray image and provided as input, the convex hull can be obtained.

RANSAC (Anonymous, 2018d) is an algorithm used to select the most supported model from many after randomly choosing sample data. In regression analysis, the difference of RANSAC and the least-square method (Anonymous, 2018b) lies in how the model parameters are found (i.e. which criteria are used). The least-square method, literally is based on the minimization of the sum of the square of errors. RANSAC picks random sample data first and then, finds model parameters that satisfy the data. After counting the amount of data closest to the model, if the number is large, the model is memorized. After repeating the process N times, the model having the largest number of supporting data is returned as the final result. Because criteria differ between these two methods, if there are many large outliers, the performance difference can be known and corrected by using RANSAC.

Convex hull and RANSAC algorithms are used to find the angles of the wrist in upright positions in an X-ray image of the left hand. By a convex hull algorithm, the feature points of wrist is found. Afterwards, moving up and down along the boundaries of wrist, the coordinates of two endpoints can be found. Thus, coordinates of the middle points of wrist can be obtained. If the obtained coordinates are given as input values, the straight lines representing the trend lines of wrist can be found. Additionally, by calculating the rotation angles, the wrist can be rotated to the upright positions.

Wrist big ROI extraction: We are currently carrying out an assessment using deep learning with the TW3 method. TW3 compares the shapes of 13 assessed bones in the left hand of a patient using the defined standards. It assigns bone classes from A-I. By calculating the sum of scores corresponding to the class of each bone, a final score is obtained and classified based on the standard table with intervals of 0.1 year units, defined according to gender. Through this, the bone age of the subject can be estimated. Deep learning is used to determine bone class. To determine the bone age correctly by training the shapes of each bone according to the class, it is necessary to extract the assessed bones in accordance with the defined standards. Therefore, before extracting the assessed bones, the 13 ROIs are extracted via. deep learning from the four big ROIs extracted for preprocessing. In this study, the big ROI extraction methodology for wrist is described especially. To confirm the accuracy and performance of this methodology, various tests are conducted and the results are analyzed.

Fig. 1: The example of left hand X-ray image

The most important reason for extracting the big ROIs from an original X-ray image is that the shapes of bones are similar. Figure 1 shows the left hand of X-ray image. From an ergonomic aspect, shapes of human bones are very similar. Even with good object detection performance using deep learning, there were difficulties in accurately finding the 13 ROIs. Thus, big ROI extraction and preprocessing should be developed.

As in Fig. 2, the wrist big ROI extraction process divides an original X-ray image into wrist region from which the 2 of 13 bones necessary for the TW3 method can be located. Preprocessing is needed because it is easier to derive 13 ROIs from big ROIs than from an entire

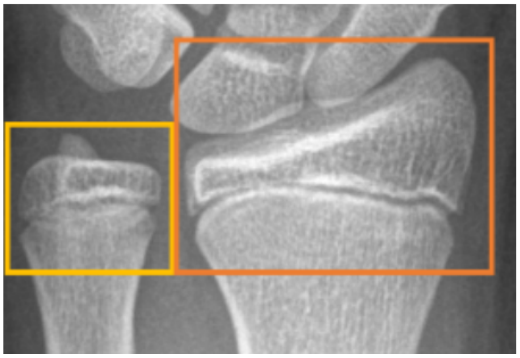

Fig. 2: The example of wrist big ROI

original X-ray image. Without preprocessing, there is a possibility that an incorrect ROI could be extracted by mistake, owing to confusion with ROIs having the same bone name. Figure 2 shows a picture of wrist big ROIs having 2 of 13 TW ROIs from an original X-ray image via. the big ROI extraction process. When the ROIs are extracted from the original X-ray using the object detection of deep learning, there is a possibility of confusion during the extraction process because of similar shapes. However, when the 13 ROIs are extracted from the big ROIs after preprocessing, the possibility of confusion is eliminated.

The big ROI extraction process for wrist is divided into two stages. In the first stage, the image is rotated, so that, the assessed bones of the ROIs are placed vertically. To find the rotation angle of the image, the trend line of corresponding bones is found using RANSAC and the inclined angle of the trend line is calculated with an arctangent function. In the second stage, the wrist big ROI regions are extracted from the original X-ray image.

Figure 3 shows the process of rotating the wrist to the upright position. The sequential explanation of this process follows. The first operation is to separate the hand and the background of the original image. To do this, we conduct image binarization. Then we blur the image using the median filter to simplify the boundaries. Figure 4 shows the binarization and median filter blurring process.

After the binarization and blurring with median filter, we have to find the center of gravity for the hand. If the center of gravity is found using OpenCV (Anonymous, 2018c), the center of gravity can be obtained. The center of gravity plays an important role because it is used as a reference point several times in the wrist big ROI extraction process.

The next step after finding the center of gravity is the trend line of the wrist. In this process, the wrist is placed in the upright position after finding the inclination of the

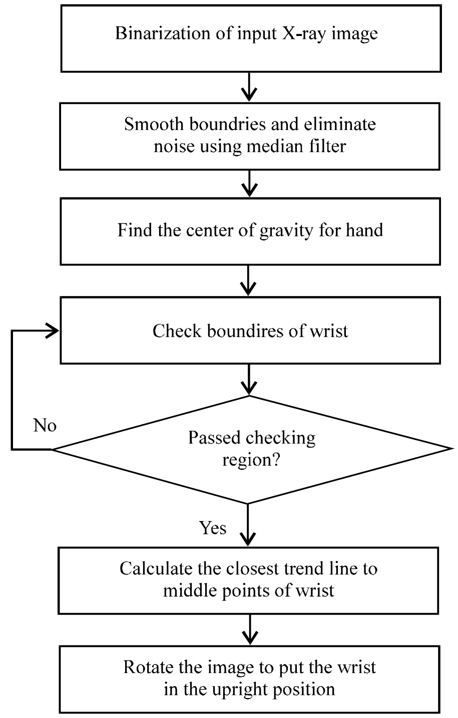

Fig. 3: The process of rotating the wrist to the upright position

wrist in the original X-ray image. The wrist is placed vertically to extract the assessed bones based on astandard. Particularly, the bones are extracted and their classes are determined via. deep learning. For these, it is necessary to apply the standard to the learning data for which better results can be obtained when images satisfying the corresponding standard are used as test data. Thus, when extracting respective bone images, the bones are placed in their upright position. To put the wrist region in upright position, an outline of the hand region is first obtained. Based on the endpoints of both sides of the outline at the bottommost part of the image, the wrist region is identified by tracing upward following the boundary lines. Tracing along the outline after calculating the distance between two end-points of the outline, the wrist region is determined at the place where the distance between two end-points becomes very large compared to the distance measured at the bottommost part. However, because there is no guarantee that the original X-ray images will always show the same shape, a limit is assigned to ensure that it does exceed the center of gravity. After identifying the wrist region, several middle points of wrist boundaries are obtained as shown in Fig. 5. Additionally, using RANSAC, a straight line closest to the middle points of the wrist boundaries is obtained. Figure 6 shows the trend line of the wrist obtained from the middle points of the wrist boundaries.

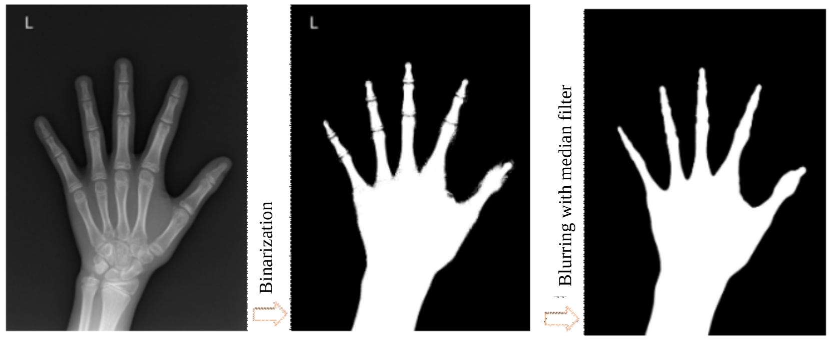

Fig. 4: The process of rotating the wrist to the upright position

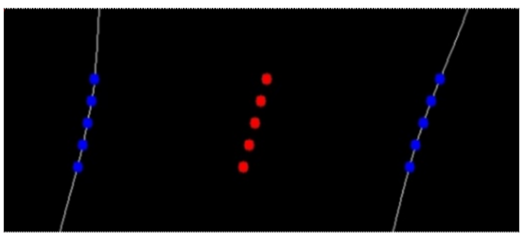

Fig. 5: Middle points of wrist boundaries

Fig. 6: A straight line obtained with the middle points of wrist

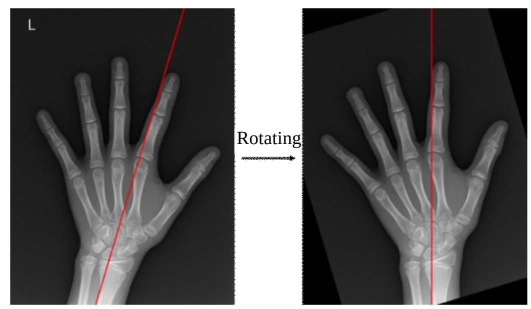

Fig. 7: A rotated image to put the trend line of wrist vertically

Figure 7 shows the image in which the wrist region is placed in the upright position by rotating the wrist's trend line vertically. The first step of finding the wrist big ROI is placing the wrist vertically.

The most important process in big ROI extraction is establishing the boundary region to be extracted. If the boundary is set incorrectly, the bones to be used for the assessment will be cut off and they will not be suitable for deep learning. Thus, if at least one bone is excluded from the 13 assessment bones, the bone age cannot be measured via. the TW3 method. Therefore, the boundary establishment of the region is very important. The explanation for establishing the boundary of the wrist region is as follows. First, the boundary of the lower part is already set. If the X-ray image is rotated to put the wrist in the upright position, the two end-point positions of wrist differ. Then, the point located higher between the two points is used as the lower boundary. If rotated in the left direction, the right endpoint is used as the lower boundary. If rotated in the right direction, the left endpoint is used and the center point of gravity in the hand region is set as the upper boundary. Figure 8, the upper red line is the line from the center of gravity of the hand and the lower red line is the line from the higher of the two end-points. This figure shows the upper and lower boundaries of the wrist big ROI.

If the upper and lower boundaries are set, the left and right boundaries must be established next. When setting the left and right boundaries, the boundary line between the hand and the background is used. The process of examining the position closest to the inside of the wrist is performed by approaching both outer sides starting from the inside of wrist within the upper and lower boundaries established earlier. Figure 9 shows the boundary of hand

Fig. 8: Setting the upper and lower boundaries of the wrist big ROI

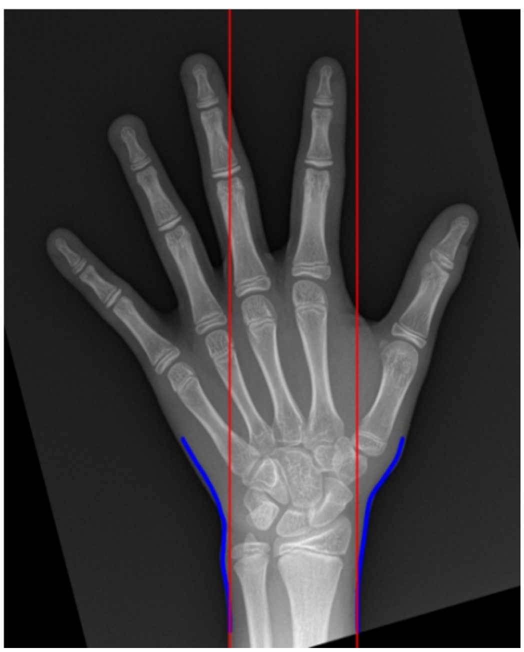

Fig. 9: Setting the left and right boundaries of the wrist big ROI

and background in the blue within the upper and lower boundaries. Using the coordinates of parts located at the innermost positions among the boundary lines, the left and right boundaries of the big ROI are set for the wrist. Once, the upper/lower/left/right boundaries are set, the wrist big ROI region can be properly extracted from the original X-ray image where the wrist is shown in the upright position.

The big ROI of the wrist can be extracted this way but an additional process is performed to lower the upper boundary somewhat based on the point located higher among the ulna and radius bones in the region. This prevents the big ROI region from being too wide, compared to the left and right boundaries. In the extracted big ROI image of the wrist because only 2 bones, the ulna and radius, exist among the 13 bones used in the TW3 method, there is no possibility of being confused with other bones.

RESULTS AND DISCUSSION

Image binarization: Because hand directions are not always inclined at the same angle as left-hand X-ray images, the big ROI extraction process is performed after vertically correcting the image with reference to the wrist, so that, the respective feature points can be easily accessed. Here, the trend line of the wrist must be found and the wrist boundaries at both sides can be known by the outlines of the hand region from the binarization process which separates the hand region and the background. The middle points of the boundaries at both sides are used to find the trend line. Here, various values were applied for the threshold value used in the binarization.

As the most common method, binarization was performed by using the average pixel value of the overall image. The result is as follows: the threshold value was the average pixel value of the overall image. (i.e., AVG) After multiplying it by a series of decimals for binarization, the results were compared with each other. Figure 10 shows the results of binarization conducted using the average pixel value of overall image as a threshold value.

To find the wrist boundary, the average pixel value for the lower part of the image was used as a threshold value. The results are shown in Fig. 11.

We confirmed that the error of recognizing the background as a hand region can be reduced when the wrist boundaries are found using the average pixel value of the lower part, rather than using the average pixel value of the overall image. Figure 11, the lower part of the image background is recognized as the hand region because the average pixel value becomes skewed closer to a dark color. The brightness of background in the X-ray image is not always consistent and the background region is relatively larger than the hand region in the upper part of the image. Therefore, using the average pixel value of the lower image part as a threshold value is effective for finding the wrist boundaries.

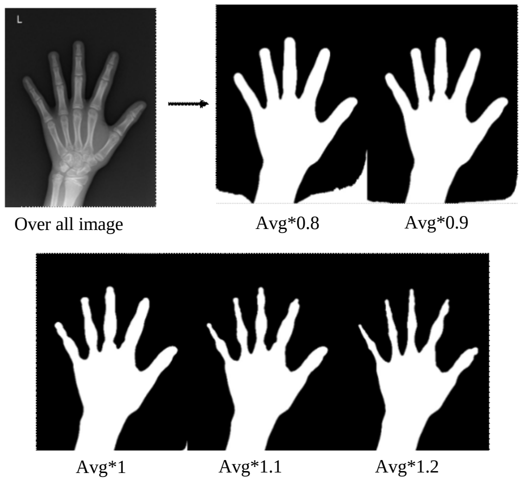

Fig. 10: Using the average pixel value of the overall image as a threshold value of binarization

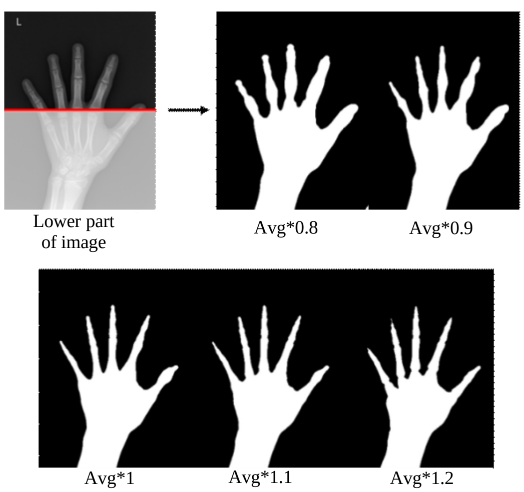

Fig. 11: Using the average pixel value of the lower part of the image as a threshold value of binarization

Finding the trend line and region of the wrist: To obtain a vertical image of the wrist, the boundaries of both ends must be found after drawing an outline in the binarization image. Approaching from the bottommost pixel on the right side of image to the left side, a part determined as the hand region is examined. When the hand region is found, the endpoint on the right side of wrist is set. Then, approaching from the endpoint of the right side to the left side, the boundary of the hand region and the background is examined, setting the left-endpoint of the wrist. Additionally, the beginning of the section for checking the middle points of the wrist is set at about 100 pixels above the bottommost position. Afterwards, ascending in the section of 100 pixels in units of 5, 10, 20 and 25 pixels, the boundary points of the wrist on both sides were obtained. Then, a trend line is obtained. To find the trend line of the wrist, the RANSAC algorithm was used. Regarding the data used as input values, the middle point coordinates of the two end-points of the wrist boundary were used for each unit in the examined section. Here, in preparation for the outlier that goes in the input data for RANSAC, one middle point was increased to 5 points, having the same y-coordinates and the x-coordinates of x–2, x-1, x, x+1 and x+2, used as input data. Figure 12 shows the method of increasing the number of points when the middle points of the wrist are used as input data for RANSAC. Figure 13 shows the trend lines obtained after finding the middle points in the section of 100 pixels for each unit. Figure 14, the trend line images of different examination units all show similar shapes and are the images of vertically rotated trend lines.

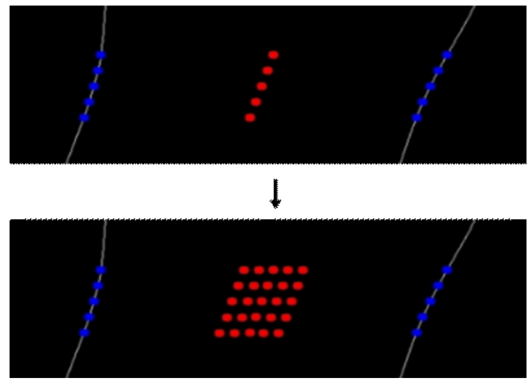

Fig. 12: Increasing the amount of input data for RANSAC

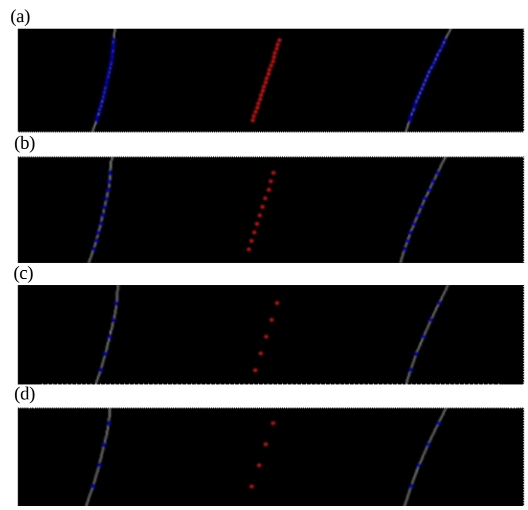

Fig. 13: Results of examining the assessed section with different units: a) 5 px; b) 10 px; c) 20 px and d) 25 px

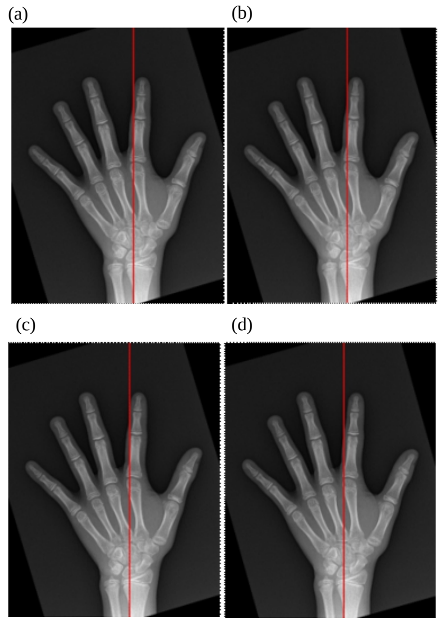

Fig. 14: Comparison of wrist trend lines and rotated images: a) 5px; b) 10 px; c) 20 px and d) 25 px

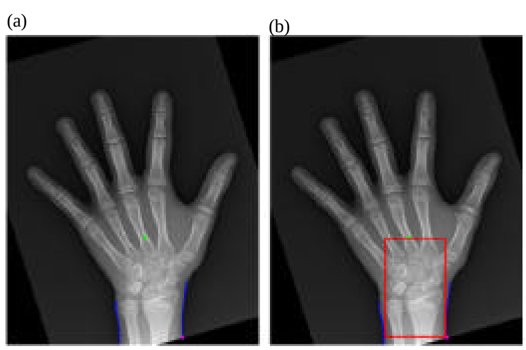

Fig. 15: a, b) Extraction of hand region using the feature points

The elements used as the boundary of the wrist region include the center point, two end-points of wrist and the boundary lines of both sides of the wrist. Figure 15 shows the feature points for hand region extraction. The green dot indicates the center point, the purple dot indicates the point located higher among the two end-points of wrist and the blue lines indicate the boundary lines on both sides of the wrist. By using them as upper/lower/left/right boundaries, the wrist region can be obtained.

CONCLUSION

In this study, a method of extracting ROIs for training data in the deep learning-based TW3 bone assessment system was studied. An X-ray image of the left hand is needed for TW3 bone-age assessment. There are total of 13 bones required in the image for the assessment. The four large regions that include the 13 assessed bones in the image are the big ROIs. To extract the wrist big ROI, various methods such as image binarization, RANSAC and image rotation were used. From the results, the learning data were composed and because of conducting the test, the maximum error of ±1 year was confirmed.

RECOMMENDATIONS

In future whereas there are many methods that can be used to reduce errors, the follow-up study should be performed by adding specific standards to extract the big ROIs more consistently. This includes training data, the most important element in deep learning.

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