

# A preliminary study for fully automated quantification of psoriasis severity using image mapping

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## ABSTRACT

Psoriasis is a common chronic skin disease and it detracts patients' QoL seriously. Since there is no known permanent cure so far, controlling appropriate disease condition is necessary and therefore quantification of its severity is important. In clinical, psoriasis area and severity index (PASI) is commonly used for abovementioned purpose, however it is often subjective and troublesome. A fully automatic computer-assisted area and severity index (CASI) was proposed to make an objective quantification of skin disease. It investigates the size and density of erythema based on digital image analysis, however it does not consider various inadequate effects caused by different geometrical conditions under clinical follow-up (i.e. variability in direction and distance between camera and patient). In this study, we proposed an image alignment method for clinical images and investigated to quantify the severity of psoriasis under clinical follow-up combined with the idea of CASI. The proposed method finds geometrical same points in patient's body (ROI) between images with Scale Invariant Feature Transform (SIFT) and performs the Affine transform to map the pixel value to the other. In this study, clinical images from 7 patients with psoriasis lesions on their trunk under clinical follow-up were used. In each series, our image alignment algorithm align images to the geometry of their first image. Our proposed method aligned images appropriately on visual assessment and confirmed that psoriasis areas were properly extracted using the approach of CASI. Although we cannot evaluate PASI and CASI directly due to their different definition of ROI, we confirmed that there is a large correlation between those scores with our image quantification method.

**Keywords:** Psoriasis, quantification of the disease, image analysis, SIFT

## 1. INTRODUCTION

Psoriasis is a common chronic skin disease. The typical symptoms of psoriasis are skin erythema, itching and generating dry silvery scales due to extraordinary accumulation of skin surface. Although psoriasis is not a fetal disease, it often makes deleterious changes on patients' appearances and decreases their QoL seriously. Unfortunately, there is no known permanent cure so far, controlling appropriate disease condition is necessary and therefore quantification of its severity is important. In clinical, Skindex<sup>1</sup> and a psoriasis area and severity index (PASI)<sup>2</sup> are commonly used for abovementioned purpose. The Skindex focuses on patients' QoL and is gleaned from a patient's questionnaire. Therefore it is subjective and not intended to quantify the disease. PASI was developed to quantize the severity of psoriasis. Severity score of each body region is diagnosed by dermatologist and the PASI is calculated by these weighted sums. It seems objective measure, however it highly depends on subjectivity of dermatologists and the score has a quite wide variety among them. In such a background, a fully automatic computer-assisted area and severity index (CASI)<sup>3</sup> was proposed to make an objective quantification of skin disease. It is simple algorithm and investigates the size and density of erythema as the most common symptom of psoriasis based on digital image analysis.

The definition of CASI is in following equation:

$$CASI = \int_{ROI} \frac{a^*(\mathbf{s}) - \bar{a}^*}{S_{ROI}} d\mathbf{s}, \quad (1)$$

where  $a^*(\mathbf{s})$ ,  $\bar{a}^*$  and  $S_{ROI}$  indicate  $a^*$  value of  $L^*a^*b^*$  color system of the target pixel  $\mathbf{s} = (x, y)$  in the ROI, average  $a^*$  value in the ROI, and the size of the ROI, respectively. Note that  $a^*$  component of  $L^*a^*b^*$  color system indicates the redness of the target.

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The CASI is calculated by (i) investigating the differences in redness of the skin between involved area and surrounding healthy normal skin areas, (ii) accumulates the differences for every pixel  $s$  in the ROI and finally (iii) normalized it by the size of ROI. Because the  $L^*a^*b^*$  color system was designed to illustrate that the difference in color space was proportional to that of psychology of vision, if a patient has the wider and/or more redness of the involved skin regions, becomes the larger score of CASI. Owing to the differential definition of CASI, it is robust over different photographic conditions such as difference in white balance, luminance etc. However, since CASI evaluates an image independently with each other, various inadequate effects caused by different geometrical conditions under clinical follow-up such as shift in direction and distance between camera and patient are not well considered. In this study, we proposed an image alignment method for clinical images and investigated to quantify severity of psoriasis under follow-up combined with the idea of CASI.

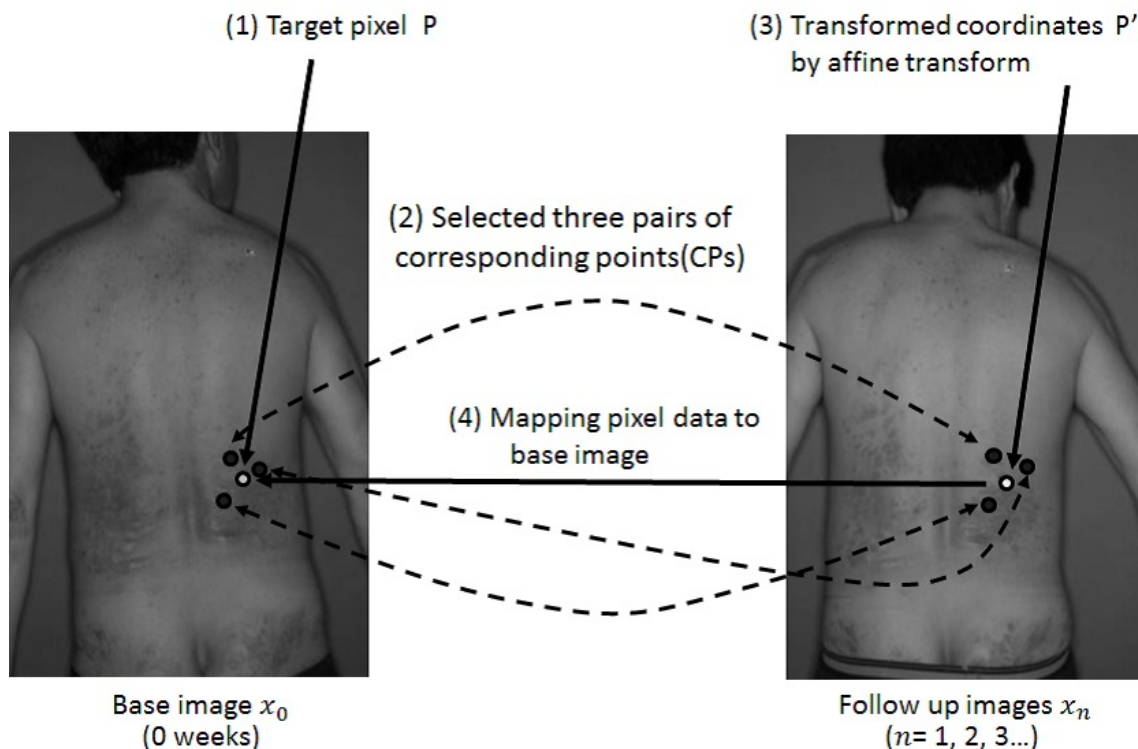


Figure 1. Schematics of pixel-based image mapping.

## 2. MATERIAL AND METHOD

In this study, we attempted to quantize the severity of psoriasis on trunk areas. We used clinical images from a total of 7 patients with psoriasis lesions on their trunk during their clinical follow-up from Keio University Hospital, Japan. In each series, we define their first image  $X_0$  as the base image and the following images  $X_n$  ( $n = 1, 2, 3, \dots$ ) obtained by their follow-up were mapped to the geometry of  $X_0$  by the proposed image alignment method. We reduced the abovementioned geometrical problems by the proposed method and quantify severity of psoriasis with CASI. As a pre-processing, we extract trunk region as the region-of-interest (ROI) from the background for each image using simple thresholding method with HSV color system. The proposed method maps images with respect to find the “same” points among images with the scale-invariant feature transform (SIFT)<sup>4</sup> and the affine transform in the ROI.

### 2.1 Detecting the corresponding points by SIFT

The diagram of the image mapping algorithm is shown in Fig. 1. Here, because the human body is not a rigid, performing an image mapping with a single affine transform is not appropriate. The proposed alignment

method maps every pixel in the ROI with affine transform whose transform matrix is estimated by three pairs of corresponding points (CPs) found by SIFT with red, green, blue and intensity channels. Now we will explain the alignment method using Fig. 1. For every target pixel  $P$  in the image  $X_0$  (1), find three pairs of CPs between images  $X_0$  and  $X_n$  ( $n = 1, 2, 3...$ ) by means of SIFT (2). The affine matrix for  $P$  is calculated with its three pairs of CPs and the target pixel  $P$  was transformed to  $P'$  in the image  $X_n$  with the affine transform (3). Finally, the pixel value of  $P'$  in  $X_n$  were mapped to the coordinates of  $P$  in the image  $X_0$  with bi-linear interpolation (4). Repeat these procedures, all pixels in the ROI of the image  $X_n$  were mapped to the geometry of the image  $X_0$ .

## 2.2 Detecting additional of corresponding points by Hough transform

The proposed method aligns images by pixel-based manner and therefore it requires enough number of CPs all over the trunk area. Here, if the number of obtained CPs between images under alignment is much fewer than required, appropriate affine transform matrix for every pixel cannot be estimated, and therefore final alignment result becomes inappropriate.

In order to relieve this issue, we added new candidates of CPs on shoulder and sides of the patient's trunk. The schematic of this algorithm is shown in Fig. 2. For all images, we estimated the shoulder lines  $l_{shoulder}^L, l_{shoulder}^R$  and the side lines of the trunk  $l_{side}^L, l_{side}^R$  by means of Hough transform. We define  $C$  that is the intersection point of two shoulder lines, i.e.  $l_{shoulder}^L$  and  $l_{shoulder}^R$ . Let  $L$  and  $R$  be also those of shoulder line and side line for the left ( $l_{shoulder}^L$  and  $l_{side}^L$ ) and as well as the right ( $l_{shoulder}^R$  and  $l_{side}^R$ ) sides, respectively. Detection example of detected CPs by SIFT (black points) and Hough transform (white points) are shown in Fig. 3. We confirmed that this additional procedure compensated for shortage of CPs.

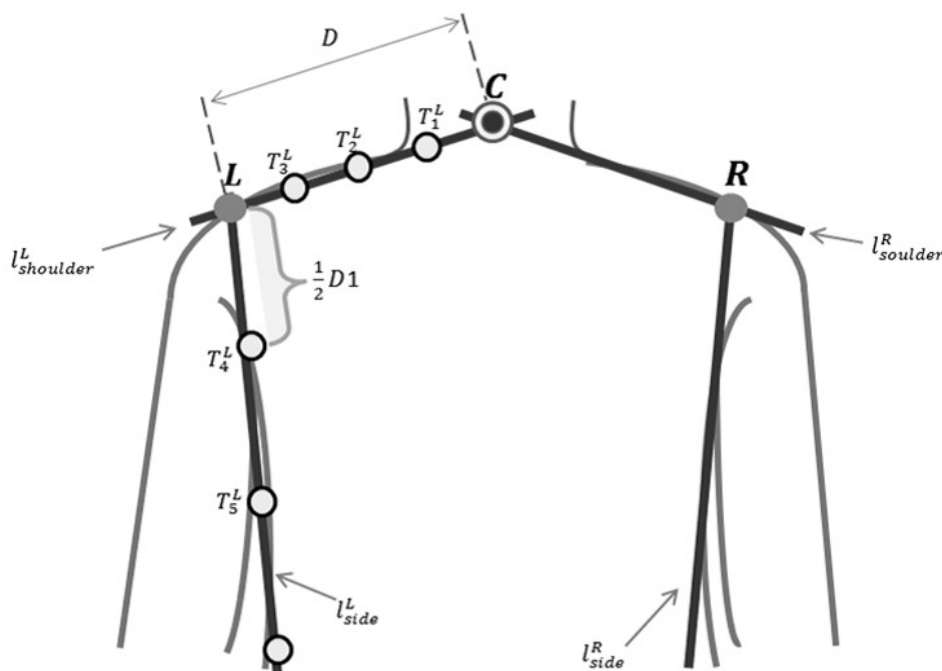


Figure 2. Detecting additional corresponding points by using Hough transform.

## 2.3 Pixel-based image mapping

As mentioned above, the proposed method maps each pixel in the image  $X_n$  to the base image  $X_0$  using affine transform and accordingly it is required to find appropriate three CPs for every pixel in the ROI (see Fig. 1(2)). Now we recall the pixel  $P$  in the image  $X_0$  and let us find its appropriate three CPs for its affine transform.

Here, in cases where the triangle formed by three CPs is too elongated or too small, the mapping procedures yields inappropriate result. This is because even slight shift of CP occurs in such situations leads serious effects

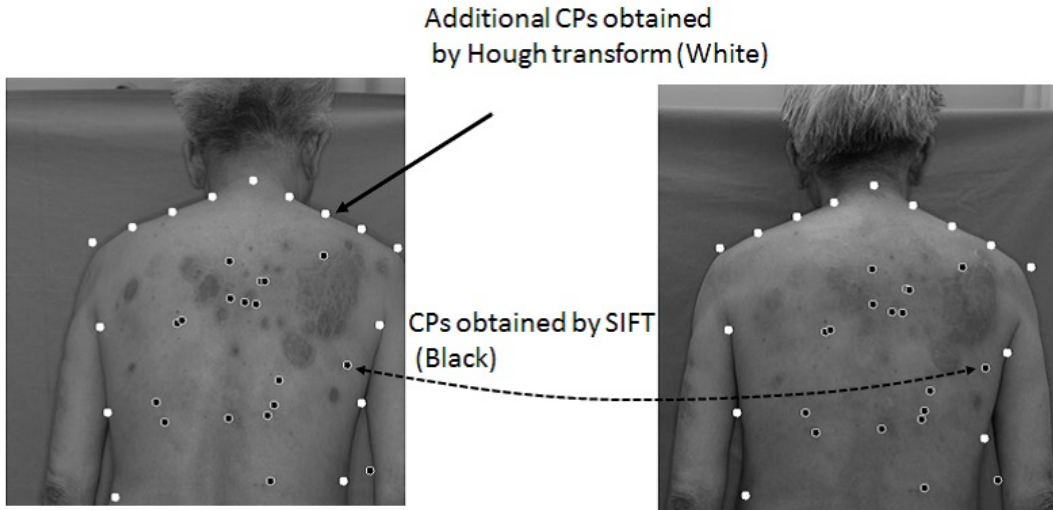


Figure 3. Obtained corresponding points (CPs) by SIFT (black) and Hough transform (white).

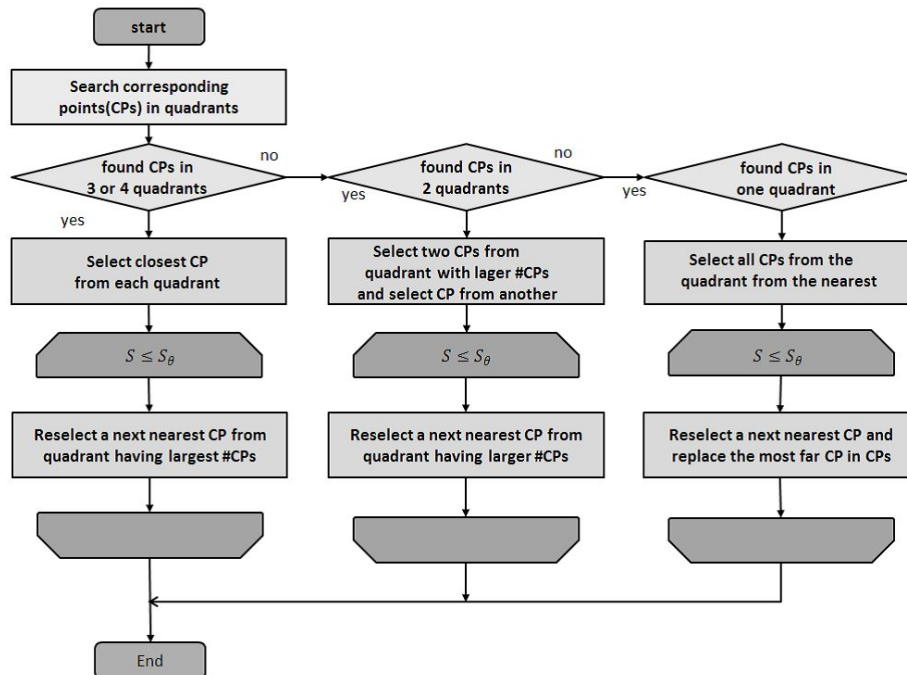


Figure 4. Flowchart of selecting proper corresponding points (CPs).

for factors of the affine matrix. On the other hand, proper mapping cannot be performed also where the size of triangle is too large. So we need to select proper three CPs for every target point  $P$ . We designed an algorithm for selecting appropriate CPs. The flowchart of the algorithm is shown in Fig. 4. The algorithm defines quadrant with the target pixel  $P$  as its origin. Select three quadrants in descending order of the number of CPs in each quadrant. In each selected quadrant, nearest CP from the target pixel  $P$  is selected and the size of formed triangle  $S$  is calculated. If the size of the triangle  $S$  is smaller than the pre-defined threshold  $S_\theta$ , reselect the CPs (i.e. select the next nearest CP from the quadrant having largest number of CPs) to fit the requirement. Note that we set  $S_\theta$  was 5% of the image size based on results by preliminary experiments. If the CPs were located only one or two quadrants, three or two points were selected from the quadrant having larger number of CPs.

After all pixels in ROIs of images  $X_n$  were mapped to the geometry of the base image  $X_0$ , quantification of the severity of psoriasis on ROI was calculated with CASI (equation (1)).

### 3. RESULTS

Fig. 5 shows sample clinical images during clinical follow-up, their mapped results with the proposed algorithm, and the extraction results of psoriasis lesions namely,  $a^*(s) - \bar{a}^*$ , respectively. We confirmed that our method mapped the patient's trunk area and detected the psoriasis lesions appropriately on visual assessment. In this case, PASI and CASI follow the similar descending trend 2.1, 1.5 to 0.3 and 2.4, 2.1 to 1.4, respectively. From Fig. 5, we confirmed the CASI with our alignment method tracked the process of remedial process appropriately. In other cases, our method also provides proper mapping results and they lead reasonable quantification results. Although we could not compare PASI and CASI directly because they have different ROIs (i.e. PASI : whole body CASI : only photographic body region), we confirmed that there was a large correlation between PASI and those scores with our image alignment method in this study.

### 4. CONCLUSIONS

In this study, we proposed a fully automated image mapping algorithm for the alignment of clinical images. The use of CASI with the proposed image alignment, we quantized the severity of psoriasis on a trial basis. We analyzed images from a total of 7 series of clinical follow-up and our algorithm attained reasonable mapping results on visual assessment and the quantification results tracked the trend of the remedial process appropriately. We consider this is one of feasibility demonstration for achieving fully automated objective quantification of skin diseases.

### ACKNOWLEDGMENTS

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### REFERENCES

- [1] Chern MM, Lasek RJ, Quinn LM, Mastow EN, Zyzanski SJ., "Skindex : a Quality-of-Life Measure for Patients with Skin Disease, Reliability, Validity, and Responsiveness," *J Invest Dermatol*, 107, 707-713 (1996).
- [2] Fredriksson T, Pettersson U., "Severe psoriasis : oral therapy with a new retinoid," *Dermatologica*, 157, 238-244, (1974).
- [3] Iyatomi H, Oka H, Hagiwara M, Miyake A, Kimoto M, Ogawa K and Tanaka M., "Computerized quantification of psoriasis lesions with color calibration Preliminary results," *Clinical and Experimental Dermatology*, 34(7), 830-833 (2009).
- [4] Lowe DG., "Object recognition from local scale-invariant features," *Proc. of IEEE International Conference on Computer Vision (ICCV)*, 1150-1157 (1999).

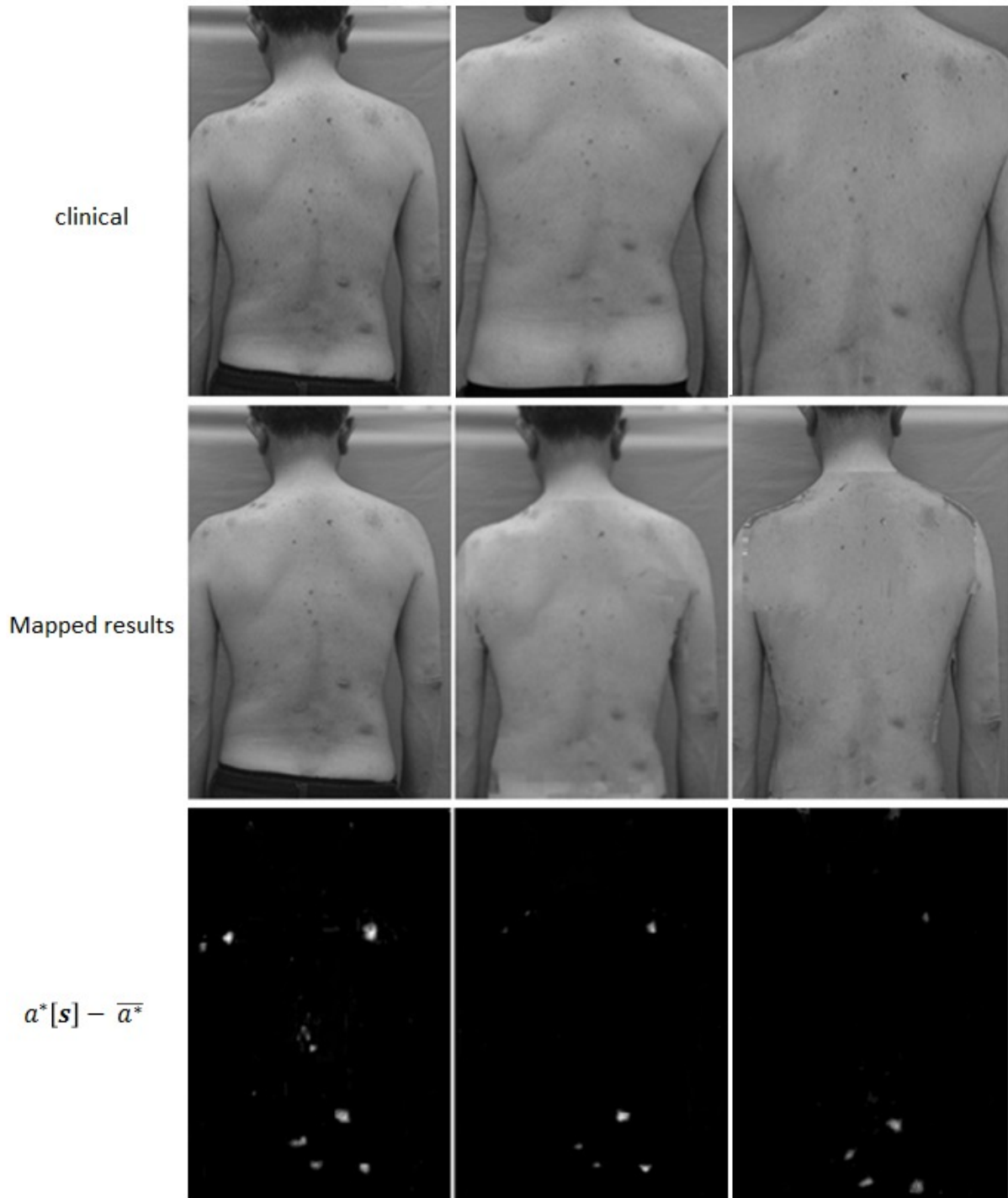


Figure 5. Top : clinical images, Middle : mapped results to the geometry of 0 weeks and Bottom : images obtained by  $a^*[s] - \bar{a}$  in Equation (1).  
 Left : 0 weeks (PASI = 2.1, CASI = 2.4 ), Center : 2 weeks later (PASI = 1.5, CASI 2.1) and Right : 4 weeks later (PASI = 0.3 , CASI =1.4)