

## Automatic Segmentation of scaling in 2-D psoriasis skin images using a semi supervised algorithm

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**Abstract:** Psoriasis is a chronic inflammatory skin disease that affects over 3% of the population. Various methods are currently used to evaluate psoriasis severity and to monitor therapeutic response. The PASI system of scoring is widely used for evaluating psoriasis severity. It employs a visual analogue scale to score the thickness, redness (erythema), and scaling of psoriasis lesions. However, PASI scores are subjective and suffer from poor inter- and intra-observer concordance. As an integral part of developing a reliable evaluation method for psoriasis, an algorithm is presented for segmenting scaling in 2-D digital images. The algorithm is believed to be the first to localize scaling directly in 2-D digital images. The scaling segmentation problem is treated as a classification and parameter estimation problem. A Markov random field (MRF) is used to smooth a pixel-wise classification from a support vector machine (SVM) that utilizes a features pace derived from image color and scaling texture. The training sets for the SVM are collected directly from the image being analyzed giving the algorithm more resilience to variations in lighting and skin type. The algorithm is shown to give reliable segmentation results when evaluated with images with different lighting conditions, skin types, and psoriasis types.

**Index Terms**— Feature extraction, Image segmentation, Markov random field(MRF), Support vector machine(SVM) , Psoriasis.

### I. Introduction

PSORIASIS is a chronic skin disease that affects an estimated 125 million people worldwide[1], which manifests as red and scaly patches of itchy skin. The scaling results from an enhanced rate of epidermal cell production manifesting anywhere from a few spots to a large area of plaque, typically found on erythema, or red inflamed skin [2].

At present there is no known cure for psoriasis and, as a consequence, much effort has been expended on treatments to control the symptoms of psoriasis. However, there is no accepted treatment for psoriasis symptoms and different physicians will treat the same symptoms differently[3]. A key factor in the improvement of psoriasis treatment is the ability to compare the efficacy of treatments across a broad range of conditions[4]. To be meaningful, such comparisons must be reliable requiring that the assessment of psoriasis severity is also reliable. Reliable tests are important to dermatologists for assessing treatments and to companies who want to improve their treatment.

Reliable and reproducible severity scores are essential for comparing psoriasis treatments and furthering psoriasis treatment research. Most, if not all [4]–[7], psoriasis assessment methods rely on a visual estimation of the area and severity of the main psoriatic symptoms of erythema and scaling. Consequently, any computer based analysis method for assessing psoriasis severity using 2D digital images must identify erythema and scaling as a precursor to further analysis.

The paper presents what I believe to be the first algorithm to automatically segment scaling directly from skin and erythema in 2-D digital images. The approach is to reduce the problem of segmenting scaling to a binary classification problem by removing erythema from consideration and then classifying the remaining pixels as either skin pixels or scaling pixels. The feature space used in the classification is derived from the color contrast between scaling and erythema, and the image texture describing the roughness of scaling which is determined by the aggregated result from a bank of Gabor filters. Our evaluation indicates that our combination of Markov random fields(MRFs) with support vector machines using an appropriate feature space can solve a wide range of scaling segmentation problems that include variations in lighting conditions, variations in skin type and variations in the types of psoriatic lesions.

## II. Feature Space For Detecting Scaling In 2-D Digital Psoriasis Images

### 2.1 A Scaling Contrast Map

A scaling contrast map is developed to enhance the contrast of scaling from erythema. The map aims to enhance the contrast of scaling especially in situations where scaling is scattered in erythema and is hard to discern visually.  $L^*a^*b^*$  Color space is used to develop a pair of multiscale center-surround filters that increase the contrast between scaling and erythema.

The  $L^*$  dimension specifies lightness where an  $L^*$  value of 0 is black and an  $L^*$  value of 100 is a diffuse white. The  $a^*$  dimension is the red–green dimension, where a positive value of  $a^*$  is red and a negative value green, and the  $b^*$  dimension is the blue–yellow dimension, where a positive value of  $b^*$  is blue and a negative value is yellow.

A scaling contrast map can be defined as follows:

$$S_{x,y} = J(L^*_{x,y}) + J(inv(a^*_{x,y}))$$

### 2.2 Texture Analysis with Gabor Filters

Gabor filters have long been used in the analysis of texture in images. Briefly, given a Gaussian distribution function  $\exp(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2})$  called the envelope, with standard deviation and spatial aspect ratio  $\gamma$ , and a complex sinusoidal  $\exp(i(\frac{2\pi x'}{\lambda} + \varphi))$  called the carrier, with spatial frequency  $1/\lambda$  and phase shift  $\varphi$  the Gabor filter is defined by

$$g(x, y; \gamma, \sigma, \lambda, \varphi) = \exp(-x'^2 + \gamma^2 y'^2 / 2\sigma^2) \exp(iy(\frac{2\pi x'}{\lambda} + \varphi))$$

The response is highest when the image intensity frequency is close to the Gabor filter. For smooth normal skin the image intensity is relatively homogeneous and is not sensitive to Gabor filters. For rougher scaly skin, the change of intensity is relatively high. Further, the choice of the standard deviation  $\sigma$  of the Gaussian envelope depends on the spatial frequency  $1/\lambda$ ,  $\sigma = 0.56\lambda$ .

### 2.3 Semi-Supervised Scaling Segmentation Algorithm

The second stage of the algorithm segments scaling from 2-D skin images through a semi-supervised algorithm to ensure the invariance of segmentation to scaling and skin changes from different patients. This part of the algorithm implements a tri- step process.

- **First:** The scaling contrast map is applied to the image and the resulting image is processed to threshold out all dark pixels representing darker pigments in the skin and including erythema, hair, moles, and other blemishes.

- **Second:** A training set for the scaling classifier is extracted from the image where the training set is composed of pixels that are highly likely to be scaling and pixels that are highly likely to be normal skin.

- **Third:** The pixels are classified using a SVM defined by the training set and the resulting image smoothed using a MRF.

### 2.4 Removing Erythema and Other Dark Pixels

The first step is to threshold out the dark pixels representing erythema, hair, moles and other blemishes using the scaling contrast map  $S$ . Scaling and normal skin pixels remain in consideration after the application of the contrast map because they result in a significantly high value of  $S$ . We define a binary image  $M$  by

$$M_{x,y} = \begin{cases} 1, & \text{if } S_{x,y} \geq t_s \\ 0, & \text{otherwise} \end{cases}$$

Where  $t_s$  is the threshold for dark pixels. Pixels labeled with 1 are retained for further analysis while pixels labeled with 0 denote darker pigments and are removed from further consideration.

### 2.5 Collecting Training Data for the Scaling Segmentation

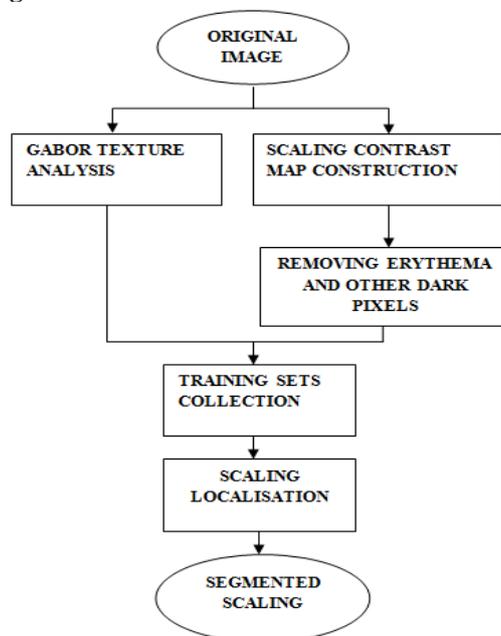
The removal of erythema and darker pixels using simplifies the problem of detecting scaling to a binary classification problem that of distinguishing scaling from normal skin. The classifier used is defined as a MRF in which the likelihood function is derived from the distance of a pixel to the hyperplane of a SVM. The parameters defining the placement of the hyperplane in feature space need to be derived using carefully chosen training data. There is a great deal of variation in skin colors and psoriasis lesions. A hyperplane using parameters derived from a generic set of training data gathered over a wide range of images is unlikely to yield good classification results. Our algorithm gathers the training data needed to place the SVM hyperplane directly from the image being analyzed. Training data is collected by identifying regions of scaling and normal skin using the position of the previously located erythema, which is often found between scaling and normal skin.

Collecting training data proceeds by first locating erythema and then using a soft-constrained -means clustering to identify candidate regions of scaling and normal skin.

### III. Proposed Algorithm

The proposed algorithm uses a bank of 24 Gabor filters designed to respond well in a variety of skin and scaling texture conditions.

#### 3.1 Proposed System Block Diagram



#### 3.2 Algorithm: An algorithm to extract a sample of scaling pixels and a sample of normal skin pixels from an image.

**Input:** The initial location of the erythema and image.

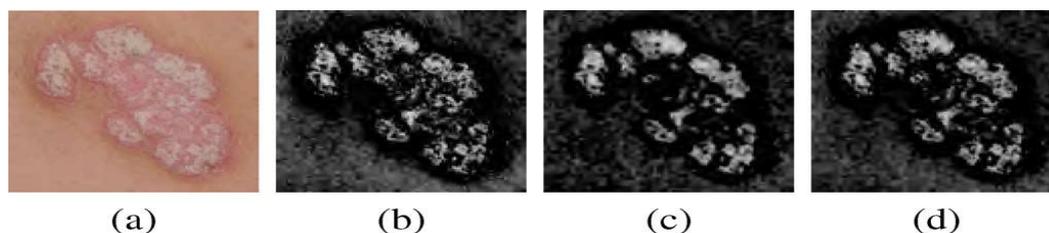
**Output:** Regions of candidate scaling pixels  $L_{scaling}$  and regions of candidate skin  $L_{skin}$  pixels.

- 1:  $n \leftarrow 0$
- 2: **repeat**
- 3:  $X \leftarrow X \oplus U$
- 4:  $n \leftarrow n + 1$
- 5: **if** an enclosed region is formed in X **then**
- 6:  $X \leftarrow FloodFill(X)$
- 7: **end if**
- 8: **until** no more enclosed region is formed
- 9:  $L_{scaling} \leftarrow M_{x,y} \cap X_{x,y} \ominus nU$
- 10:  $L_{skin} \leftarrow M_{x,y} \cap X_{x,y}^c$
- 11: **return**  $L_{scaling}, L_{skin}$

### IV. Experiments And Results

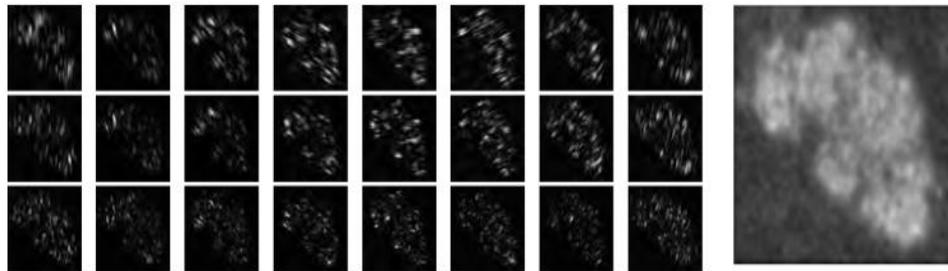
**Figure 1:**

Scaling contrast map construction.(a) Original image. (b) Contrast map derived from  $L^*$  (c) Contrast map derived from  $a^*$  (d) Scaling contrast map.



**Figure 2:**

Texture examination corresponding to the original image in Fig .Gabor filtering responses from a bank of Gabor filters(the spatial frequency changes along the row and the rotation angle changes along the column).  
(b) The final Gabor feature image.



## V. Conclusion

The result indicates that this algorithm makes progress towards the aim of automatic scaling segmentation. Scaling localization is implemented by a semi-supervised classification in this study. Two features are used: one is the scaling contrast map, which enhances the conspicuousness of scaling against erythema, and the other is a Gabor feature, which differentiates between scaling and normal skin based on image texture. Training sets for the classification are collected by a soft constrained K-means to avoid the human interference. The proposed algorithm shows good performance as is presented in the specificity and dice evaluation. Even though the sensitivity analysis is weaker, the total accuracy from the dice evaluation is always stronger. Moreover, when we compare the algorithm to manually collected training sets, the proposed method presents a slightly weaker sensitivity to the SVM and the MRF. However, better specificity and dice evaluation are achieved when compared to the SVM and the MRF. Notice that the specificity and dice measurements of our method are very close to the case for training sets that are manually selected. This result validates the performance of the soft-constrained k-means, through which the training sets, are automatically collected.

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