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# Segmentation of Scaling in Psoriasis

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***Abstract*— Psoriasis is an immune-mediated disease that affects the skin. Scaling typically appears as white or creamy colored scales on regions of red and inflamed skin (erythema) but can also appear in isolation without the accompanying erythema. Psoriasis Area and Severity Index is the most widely used tool for the measurement of severity of psoriasis .These scores are estimated by inspecting the psoriatic lesions visually and relying on the clinicians' expertise to derive meaningful scores. It is possible for two clinicians to derive two different severity scores using the same scoring technique for the same psoriatic lesion .In this project, as an integral part of developing a reliable evaluation method for psoriasis, an algorithm is presented for segmenting scaling in 2-D digital images. This algorithm is composed of two main stages: a feature extraction stage and a scaling segmentation stage. The algorithm analyses skin color using an appropriately chosen color space and uses a bank of Gabor filters to describe the textures that correlate strongly with scaling. A scaling contrast map is developed to enhance the contrast of scaling from erythema. The algorithm next removes erythema pixels from consideration and resamples the image to collect training samples for the classification process. The scaling contrast map is applied to the image and the resulting image is processed to thresh-hold out the erythema. 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. The pixels are classified using a support vector machine defined by the training set and the resulting image smoothed using a Markov random field.**

***Index terms*- Feature extraction, image segmentation, Markov random field (MRF), psoriasis, support vector machine (SVM).**

## I. INTRODUCTION

Image processing refers to processing of a 2D picture by a computer.

An image defined in the "real world" is considered to be a function of two real variables, for example, a(x,y) with a as the amplitude (e.g. brightness) of the image at the real coordinate position (x,y). Before going to processing an image, it is converted into a digital form. The various image processing techniques are Image enhancement, Image restoration, Image analysis, Image compression, Image synthesis.

Image enhancement operations improve the qualities of an image like improving the image's contrast and brightness characteristics, reducing its noise content, or sharpen the details. This just enhances the image and reveals the same information in more understandable image. It does not add any information to it. Image restoration like enhancement improves the qualities of image but all the operations are mainly based on known, measured, or degradations of the original image.

Image restorations are used to restore images with problems such as geometric distortion, improper focus, repetitive noise, and camera motion. It is used to correct images for known degradations. Image analysis operations produce numerical or graphical information based on characteristics of the original image. They break into objects and then classify them. They depend on the image statistics. Common operations are extraction and description of scene and image features, automated measurements, and object classification. Image analyse are mainly used in machine vision applications.

Image compression and decompression reduce the data content necessary to describe the image. Most of the images contain lot of redundant information, compression removes all the redundancies. Because of the compression the size is reduced, so efficiently stored or transported. The compressed image is decompressed when displayed.

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Lossless compression preserves the exact data in the original image, but Lossy compression does not represent the original image but provide excellent compression. Image synthesis operations create images from other images or non-image data.

*A. An Overview of the Algorithm*

Psoriasis is a chronic skin disease that affects an estimated 125 million people worldwide, which manifests as red and scaly patches of itchy skin. Scaling typically appears as white or creamy colored scales on regions of red and inflamed skin (erythema) but can also appear in isolation without the accompanying erythema. 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. 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. A key factor in the improvement of psoriasis treatment is the ability to compare the efficacy of treatments across a broad range of conditions. 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 treatments.

Currently, psoriasis severity is assessed by deriving a severity score. The most widely used is the PASI score based on the area and severity of erythema, the area and severity of the creamy colored flaky skin, or scaling, in the lesions and the thickness of the lesion. It is possible for two clinicians to derive two different severity scores using the same scoring technique for the same psoriatic lesion. Reliable and reproducible severity scores are essential for comparing psoriasis treatments and furthering psoriasis treatment research.

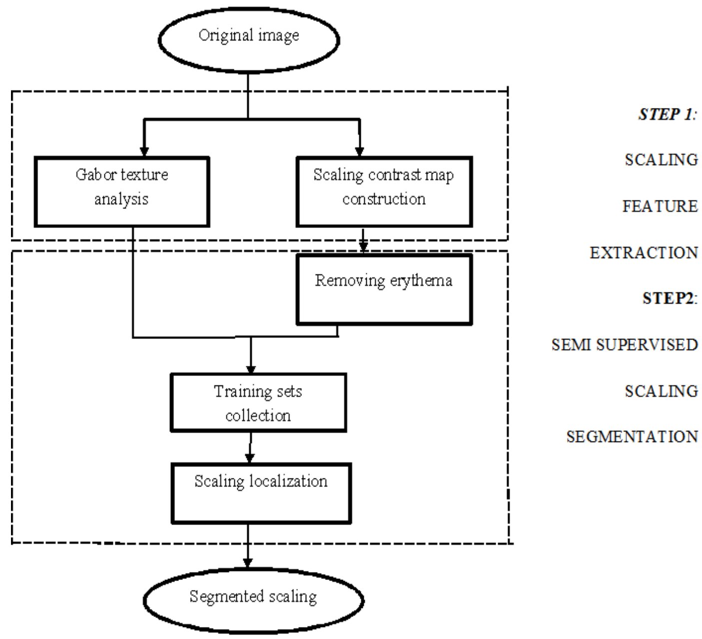


**Fig. 1. Flowchart of the algorithm for segmentation of scaling in 2-D psoriasis skin images.**

This project is believed 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.

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A combination of Markov random fields 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.

Scaling typically appears as white or creamy colored scales on regions of red and inflamed skin (erythema) but can also appear in isolation without the accompanying erythema. When psoriasis appears without the accompanying erythema it appears as discernibly white or creamy flakes on normal skin.

Scaling can present as small spots or as patches scattered within erythema. The color of scaling may be very similar to that of normal skin, especially if the skin is fair, making it difficult to differentiate between scaling and normal skin using on color alone. However, the rough textured surface of scaling is markedly different from normal skin. The algorithm uses a feature space derived from both color and texture to classify pixels.

The algorithm is composed of two main stages: a feature extraction stage and a scaling segmentation stage. The algorithm first analyses skin color and skin texture using an appropriately chosen color space and bank of Gabor filters to create a feature space for the image. The algorithm next removes erythema pixels from consideration and resamples the image to collect training samples for the classification process. The segmentation is achieved by using a Markov random field and the hyperplane derived from a support vector machine.

### *B. The Computer Assisted Scoring of Psoriasis Severity*

The computer assisted analysis of psoriasis lesions has received significant attention in recent years, but most of the work has focused on segmenting psoriasis lesions from normal skin and specifically for plaque psoriasis. The problem of segmenting scaling has received much less attention. Röing, Jacques, and Kontinen [8] provide an interactive method for segmenting psoriasis lesions from normal skin using color thresholding. Gomez et al. [9] apply a quadratic discriminant analysis to separate psoriasis lesions based on a color analysis. However, both of these methods are not robust to disturbances caused by shadows. Taur et al. [10] use texture and color analysis in combination with a neuro-fuzzy classifier to segment psoriasis lesions, but not scaling.

The color features are derived from the hue and saturation components in the image and the texture features of skin is graded according to a fuzzy texture spectrum. A key feature of [10] is that the training sets are derived from the image using a moving window to find homogeneous regions of normal skin and psoriasis. The algorithm is improved in [11] to decrease the computational complexity. The drawback of the Taur et al. algorithm is in the localization of homogenous regions in the selection of training data. The method for identifying homogeneous regions is reliable for large window sizes but is less accurate detecting small spot- shaped psoriasis lesions.

## II. FEATURE SPACE FOR DETECTING SCALING IN 2-D DIGITAL PSORIASIS IMAGES

### *A. 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 multi-scale center-surround filters that increase the contrast between scaling and erythema. The L* dimension specifies lightness where L* an 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. The color of scaling correlates well with higher values of L* and erythema with positive values of a*.

Shadows result in smaller L* values but do not necessarily affect the other dimensions. Furthermore, by inverting the dimension the color difference between scaling and the surrounding erythema or skin can be increased. With this in mind a scaling contrast map can be defined as follows:

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

Where $S_{x,y}$ is the value of scaling contrast filter at the image coordinate (x,y).

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*B. Texture Analysis with Gabor Filters*

The scaling contrast map behaves well when segmenting scaling from erythema but is not sufficient for segmenting scaling from normal skin, especially when the color difference between the two is small. Scaling presents as a rough textured surface in 2-D images that distinguishes it from the more smoothly textured normal skin. The rough texture of scaling combined with the scaling contrast map provides a good combination of features for segmenting scaling. An image texture is a set of metrics calculated in image processing designed to quantify the perceived texture of an image.

Image Texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image.

Image textures can be artificially created or found in natural scenes captured in an image. Image textures are one way that can be used to help in Segmentation (image processing) or classification of images. To analyze an image texture in computer graphics, there are two ways to approach the issue: Structured Approach and Statistical Approach.

- *Structured Approach:*

A structured approach sees an image texture as a set of primitive texels in some regular or repeated pattern. This works well when analyzing artificial textures. To obtain a structured description a characterization of the spatial relationship of the texels is gathered by using Voronoi tessellation of the texels.

- *Statistical Approach:*

A statistical approach sees an image texture as a quantitative measure of the arrangement of intensities in a region. In general this approach is easier to compute and is more widely used, since natural textures are made of patterns of irregular subelements. Texture analysis might be applied to various stages of the process. At the preprocessing stage, images could be segmented into contiguous regions based on texture properties of each region; At the feature extraction and the classification stages, texture features could provide cues for classifying patterns or identifying objects.

As a fundamental basis for all other texture-related applications, *texture analysis* seeks to derive a general, efficient and compact quantitative description of textures so that various mathematical operations can be used to alter, compare and transform textures. Most available texture analysis algorithms involve extracting texture features and deriving an image coding scheme for presenting selected features. These algorithms might differ in either which texture features are extracted or how they are presented in the description. For example, a statistical approach describes a texture via image signal statistics which reflect nondeterministic properties of spatial distribution of image signals.

A spectral method extracts texture features from the spectral domain. A structural approach considers a texture as a hierarchy of spatial arrangements of well-defined texture primitives. A probability model describes the underlying stochastic process that generates textures. Four major application domains related to texture analysis are texture classification, texture segmentation, shape from texture, and texture synthesis.

Texture classification assigns a given texture to some texture classes. Two main classification methods are supervised and unsupervised classification. Supervised classification is provided examples of each texture class as a training set. A supervised *classifier* is trained using the set to learn a characterisation for each texture class. Unsupervised classification does not require prior knowledge, which is able to automatically discover different classes from input textures. Another class is *semi-supervised* with only partial prior knowledge being available.

The majority of classification methods involve a two-stage process. The first stage is feature extraction, which yields a characterisation of each texture class in terms of feature measures. It is important to identify and select distinguishing features that are invariant to irrelevant transformation of the image, such as translation, rotation, and scaling.

Ideally, the quantitative measures of selected features should be very close for similar textures. However, it is a difficult problem to design a universally applicable feature extractor, and most present ones are problem dependent and require more or less domain knowledge.

The second stage is classification, in which classifiers are trained to determine the classification for each input texture based on obtained measures of selected features. In this case, a classifier is a function which takes the selected features as inputs and texture classes as outputs.

Texture segmentation partitions an image into a set of disjoint regions based on texture properties, so that each region is homogeneous with respect to certain texture characteristics. Results of segmentation can be applied to further image processing and analysis, for instance, to object recognition. Similar to classification, segmentation of texture also involves extracting features and deriving metrics to segregate textures. However, segmentation is generally more difficult than classification, since boundaries that separate different texture regions have to be detected in addition to recognising texture in each region.

Texture segmentation could also be supervised or unsupervised depending on if prior knowledge about the image or texture class is available. Supervised texture segmentation identifies and separates one or more regions that match texture properties shown in the training textures. Unsupervised segmentation has to first recover different texture classes from an image before separating them into regions. Compared to the supervised case, the unsupervised segmentation is more flexible for real world applications despite that it is generally more computationally expensive.

Partitioning an image into homogeneous regions is very useful in a variety of applications of pattern recognition and machine leaning. For example, in remote sensing and GIS analysis, texture segmentation could be applied to detect landscape change from an aerial photo. Shape from texture is the problem of estimating a 3D surface shape by analysing texture property of a 2D image. Weak homogeneity or isotropy of a texture is likely to provide a shape cue.

For instance, texture gradient is usually resulted from perspective projection when the surface is viewed from a slant, which infers the parameters of surface shape or the underlying perspective transformation. Therefore, via a proper measure of texture gradient, a depth map and the object shape could be recovered.

Shapes from texture have been used for recovering true surface orientation, reconstructing surface shape, and inferring the 3D layout of objects, in many applications.

For example, the plane vanish line could be computed from texture deformation in an image, which could be used to affine rectify the image. Texture synthesis is a common technique to create large textures from usually small texture samples, for the use of texture mapping in surface or scene rendering applications. A synthetic texture should differ from the samples, but should have perceptually identical texture characteristics. The main advantage of texture synthesis in this case is that it can naturally handle boundary condition and avoid verbatim repetitions. In computer vision, texture synthesis is of interest also because it provides an empirical way to test texture analysis. Because a synthesis algorithm is usually based on texture analysis, the result justifies effectiveness of the underlying models.

Compared to texture classification and segmentation, texture synthesis poses a bigger challenge on texture analysis because it requires a more detailed texture description and also reproducing textures is generally more difficult than discriminating them. Other applications of texture synthesis include image editing, image completion, and video synthesis, etc. The variation in the textures of scaling and in the textures of normal skin in different lesions and in different people makes the choice of one single Gabor filter unlikely.

The algorithm uses a bank of 24 Gabor filters designed to respond well in a variety of skin and scaling texture conditions. The frequencies and rotations are chosen based on the computational modelling of the primary visual cortex on texture analysis. The bank of Gabor filters are applied to the image and the results integrated into a single Gabor texture image.

First, the square of Gabor energy image is filtered using a hyperbolic tangent to narrow the range. A mean filter is then used to smooth the images with a window size equal to wavelength of the current Gabor filter being integrated. Finally, the Gabor texture image is obtained by summing the smoothed output over all of the rotation angles and frequencies of the Gabor filters.

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## III. 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 thresh-hold 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.

### *A. 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 .

### *B. Collecting Training Data for the Scaling Segmentation :*

The removal of erythema and darker pixels 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 hyper- plane 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. The 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-con- strained -means clustering to identify candidate regions of scaling and normal skin.

1. *An Approximate Localization of Erythema*: The location of erythema is identified by gray-scale intensity using the scaling contrast map where low values are indicating red pixels; normal skin would show negative values in the scaling contrast map.
2. *Obtaining a Sample of Scaling and Skin Pixels:* Localization of erythema is to collect a sample of skin pixels and scaling pixels. Using the fact that scaling is often surrounded, or partially surrounded, by erythema; we use dilation and erosion operations to create regions of scaling enclosed by boundaries of erythema. Regions within the boundaries thus created are filled using a flood fill operation.
3. *Soft-Constrained K -Means Clustering*: The algorithm uses a soft-constrained K-means clustering to select training data from the candidate sets $L_{scaling}$ and $L_{skin}$.

### *C. Segmenting Scaling From Normal Skin*

#### *1) The Support Vector Machine:*

SVMs are common technique for solving classification problems. The aim for the basic SVM is to find a hyperplane that separates a data set into one of two predefined classes. The hyperplane is defined using training data to estimate the hyper- plane parameters so that the distance to any training sample is maximized. If a hyperplane can be found that separates the two training sets then they are said to be linearly separable.

In general, however, we cannot assume that a class of scaling and skin pixels sampled from an arbitrarily chosen image will be linearly separable.

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In this case the well-known kernel trick is used, where the training data is embedded into a higher dimensional space by using a kernel function that preserves the properties of the training sets under the embedding.

*2) The Markov Random Field to Classify Pixels:*

SVMs can be used to solve a wide class of scaling from skin segmentation problems. However, when scaling and normal skin occur at psoriasis lesion boundaries, the classification more often de- pends on the image structure and the neighborhood of the pixel being classified than on clear distinctions in feature space. An MRF is formulated precisely with this type of problem in mind. The proposed algorithm generates an SVM to provide an initial classifier that the MRF then uses to smooth the region located by the SVM.

Segmentation of scaling from normal skin is done using the Support Vector Machine (SVM) and Markov random Field (MRF) algorithms. SVM is used to provide an initial classifier that the MRF then uses to smooth the region located by the SVM. SVMs can be used to solve a wide class of scaling from skin segmentation problems. However, when scaling and normal skin occur at psoriasis lesion boundaries, the classification more often depends on the image structure and the neighborhood of the pixel being classified than on clear distinctions in feature space.

A combination of Markov random fields 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.

## IV. CONCLUSION

In this paper, a general framework for automatic localizing scaling in psoriasis images is presented. The result indicates that our 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-means to avoid the human interference. At the end, we combine the advantages of the SVM and the MRF to separate scaling from skin images.

The SVM shows good performance in classification, but does not involve spatial information. Normal skin pixels around psoriatic lesion boundaries exhibit similar texture features to scaling, and are usually misclassified by the SVM. By integrating the SVM into our adaptation of the MRF, the internal structures of images are considered and that increases the classification accuracy. The results from our method are compared with the traditional SVM and the MRF.

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 -means, through which the training sets are automatically collected.

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