I. INTRODUCTION

Psoriasis is a common skin disease with no known cure. It is both subjective and time consuming to evaluate the severity of psoriasis lesions using manual methods. More objective automated methods are in great demand in both psoriasis research and in clinical practice. Chronic diseases are non-contiguous and it requires special therapy to maintain the health. Psoriasis is an uncomfortable, unsightly skin condition and it often painful and intensely itchy chronic disease.

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. PASI scores are estimated by inspecting the psoriatic lesions visually and relying on the clinicians’ expertise to derive meaningful scores. The result is unavoidable inter- and intra-observer difference in severity scores. 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. Most, if not all 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 2-D digital images must identify erythema and scaling as a precursor to further analysis.

The paper presents what we 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.

A. An Overview of the Algorithm

In our paper we are going to deal in detail about MRF, SVM, SRG, ASRG algorithms…

MRF: Human skin detection is performed using a new color space coordinate and a Markov random field based approach. The proposed color space uses a variant of the principal component analysis
technique to reduce the number of color components. The MRF model takes into account the spatial relations within the image that are included in the labeling process through statistical dependence among neighboring pixels. Since only two classes are considered the Ising model is used to perform the skin/non-skin classification process.

**SVM:** The methodology is based on the support vector machines algorithm for data classification and it has been applied to the problem of the recognition of malignant melanoma versus dysplastic naevus. Border and colour based features were extracted from digital images of skin lesions acquired under reproducible conditions, using basic image processing techniques. Two alternative classification methods, the statistical discriminant analysis and the application of neural networks were also applied to the same problem and the results are compared. Results: The SVM (Support Vector Machines) algorithm performed quite well achieving 94.1% correct classification, which is better than the performance of the other two classification methodologies. The method of discriminant analysis classified correctly 88% of cases (71% of Malignant Melanoma and 100% of Dysplastic Naevi), while the neural networks performed approximately the same.

Conclusion: The use of a computer-based system, like the one described in this paper, is intended to avoid human subjectivity and to perform specific tasks according to a number of criteria. However the presence of an expert dermatologist is considered necessary for the overall visual assessment of the skin lesion and the final diagnosis.

**SRG:** We propose a new automatic image segmentation method. Color edges in an image are first obtained automatically by combining an improved isotropic edge detector and a fast entropic thresholding technique. After the obtained color edges have provided the major geometric structures in an image, the centroids between these adjacent edge regions are taken as the initial seeds for seeded region growing (SRG). These seeds are then replaced by the centroids of the generated homogeneous image regions by incorporating the required additional pixels step by step. Moreover, the results of color-edge extraction and SRG are integrated to provide homogeneous image regions with accurate and closed boundaries. We also discuss the application of our image segmentation method to automatic face detection. Furthermore, semantic human objects are generated by a seeded region aggregation procedure which takes the detected faces as object seeds.

**ASRG:** We present an automatic seeded region growing algorithm for color image segmentation. First, the input RGB color image is transformed into YCbCr color space. Second, the initial seeds are automatically selected. Third, the color image is segmented into regions where each region corresponds to a seed. Finally, region-merging is used to merge similar or small regions. Experimental results show that our algorithm can produce good results as favorably compared to some existing algorithms.

![Fig. 1. Examples of scaling in psoriasis lesions.](image)

(a) Scattered scaling in plaque psoriasis. (b) Patched scaling in plaque psoriasis. (c) Extensively covered scaling in plaque psoriasis. (d) Scaling in guttate psoriasis. (e) Scaling in pustular psoriasis. (f) Scaling in erythrodermic psoriasis.

### II. SYSTEM ARCHITECTURE

![System Architecture Diagram](image)

### III. 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. Color space is used to develop a pair of multi-scale center-surround filters that increase the contrast between scaling and erythema. The dimension specifies lightness where an value of 0 is black and an value of 100 is a diffuse white. The dimension is the red-green dimension.
where a positive value of is red and a negative value green, and the dimension is the blue-yellow
dimension, where a positive value of is blue and a
negative value is yellow. The color of scaling
correlates well with higher values of and erythema
with positive values of . Shadows result in smaller
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:

\[ S(x,y) = J(L^*(x,y) + J(in(a^*(x,y))) \quad (1) \]

Where \( S(x,y) \) is the value of scaling contrast filter \( S \) at
the image coordinate \((x,y)\), \( J() \) is a multi-scale center-
surround filter that detects contrast, and \( in(a^*) \)
inverts the image in the \( a^* \) dimension and is defined
by \( in(a^*(x,y)) = \max(i,j)[a^*(i,j)-a^*(x,y)] \) where \((i,j)\) runs
through all the coordinates in the image.

B. Texture Analysis With Gabor Filters

The scaling contrast map \( S \) behaves well when
segmenting scaling from erythema but is not
sufficient for segmenting scaling from normal skin,
specialy 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.

![Texture examination corresponding to the original
dermatograph in Fig. 2. (a) 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.](image)

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

\[ G(x,y,r,\psi) = \exp(y^*(x^2+r^2y^2)/2) \exp(y(2\pi x^*+\psi)) \quad (2) \]

Where \( x = \cos \psi + y \sin \psi \) and \( y = x \sin \psi + y \cos \psi \), is the
rotation angle. The response of the Gabor filter is
obtained by computing the convolution of the filter
with the image, where is the set of image points.
The response has both real and complex parts that we
denote here by and  . The Gabor energy is defined as
the magnitude of the Gabor filter response . We use
the square of the Gabor energy because it is better in
accentuating the differences between scaling and
normal skin than the more commonly used Gabor
energy. 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 of the Gaussian envelope depends on the
spatial frequency , \( \psi \) is based on the assumption that
each texture contains its highest energy in a narrow
frequency. The variations 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.

C. 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. Scaling and
normal skin pixels remain in consideration after the
application of the contrast map because they result
in a significantly high value of . We define a binary
image by where is the threshold for dark pixels.
Pixels labelled with 1 are retained for further analysis while
pixels labelled with 0 denote darker pigments and are
removed from further consideration.

D. 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.

1) An Approximate Localization of Erythema: The
location of erythema is identified by gray-scale
intensity using the scaling contrast map where low
values of indicate red pixels. A rough segmentation of erythema, but one that serves our purposes, can be obtained by empirically labelling a pixel to be erythema if. This is because darkened normal skin would show negative values in the scaling contrast map, but would still be greater than the values of erythema.

2) Obtaining a Sample of Scaling and Skin Pixels: The next step is to use the approximate localization of erythema 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 an operation.

Moreover Dice’s coefficient is much higher for the combined classifier than either the SVM or the MRF indicating higher similarity between the sets of scaling pixels and nonscaling pixels as found by the combined classifier and the “ground truth.”

The comparison of classification results from the training sets selected by the soft-constrained -means and the manually selected sets indicates a difference as well. The manually selected training set has a higher specificity and dice for the MRF and has a higher dice for the SVM. Additionally, for the proposed method the difference between the two groups of training sets in the specificity and the dice is not very big. When the measures do not show a clear advantage for one method over another in terms of results then the automated method where human intervention is not required is to be preferred.

In addition, that indicate the performance of the proposed algorithm is still encouraging when the dataset covers the changes of skin types and spectral sensitivity of the camera. This is from the contribution of collecting training sets from individual images. These global changes do not disturb the performance of the proposed algorithm. The results show the robustness of the proposed algorithm against shadows, hair, wrinkles, and changes of imaging environment. The dice measurement for our method is always higher than the other two classifiers where manually selected training sets are used. In all cases either sensitivity or specificity for our method is highest as well.

The use of the contrast map enables our algorithm to differentiate scaling from shadows, images captured in high illumination and images captured in low illumination. The changes of imaging direction do not affect the segmentation results, even though the lighting condition changes in this situation. In addition, our algorithm shows robustness to wrinkles and skin with short hair. This is a contribution by the Gabor features. The designed bank of Gabor filters is good at characterizing the difference of scaling from wrinkles and short hair, due to the use of multiple scales and orientations. However, when the hair is long and clear in the image, the Gabor features fail to suppress the disturbance.

In our future work, researching the hair removal algorithm, such as the conventional Dull Razor algorithm, which is especially useful for removing the long and thick hairs, will be included. Also, the feature space related to texture analysis can be improved and this will also form part of our future work. In future we will test the algorithm against more images in the database with clinic experts to locate the ground truth. The experimental results illustrated in the Fig 3.
A limitation of the validation is the possibility that the ground truth is not accurately marked. A manual procedure for segmenting scaling is prone to error especially for small regions of scaling skin that are not obviously distinguishable from the surrounding normal skin.

IV. PROPOSED SYSTEM

The paper presents what we believe to be the first algorithm to automatically segment scaling directly from skin and erythema in 2D Digital images. The approach is to reduce the problem of segmenting 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. The segmentation is achieved by using a MRF and hyperplane derived from a support vector machine(SVM). For improving the quality of image we used SRG (Seeded Region Growing) techniques.

CONCLUSION

In this paper, we present a general framework for automatic localizing scaling in psoriasis images. 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 structure 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.

REFERENCES