An Analysis of Psoriasis Skin Images

Ashwini C. Bolkote, M.B. Tadwalkar

Abstract— In this study a skin disease diagnosis system was developed and tested. The system was used for diagnosis of psoriases skin disease. Present study relied on both skin color and texture features (features derives from the GLCM) to give a better and more efficient recognition accuracy of skin diseases. In this study feed forward neural networks is used to classify input images to be psoriases infected or non psoriasis infected.

Index Terms— Skin recognition, skin texture, computer aided disease diagnosis, texture analysis, neural networks, Psoriasis.

I. INTRODUCTION

With advance of medical imaging technologies (including instrumentation, computer and algorithm), the acquired data information is getting so rich toward beyond the humans capability of visual recognition and efficient use for clinical assessment. Human skin is a complex surface, with _ne scale geometry that makes its appearance difficult to model. Slight changes of pigment construction in skin may cause a rich variation in skin color. By analyzing the skin texture, a lot of observations can be made regarding the nature and coarseness of the skin. Skin diseases, if not treated earlier might lead to severe complications in the body including spreading of the infection from one individual to the other.

Human ability is the best one but, not possible to analyze the complex information. CAD is the best diagnosis which is helpful to the recognize and efficient to use for clinical assessment. CAD technology can see some details inside the images. CAD diagnosis proven to be very helpful and many system where used to help in the diagnosis of many diseases. The concept of computer or ideal interpreter has been around for many years. Computer technologies can make somewhat simple abnormality detection and disease diagnosis from the images, but could not replace the human ability to analyze complex information. On the other hand, computer technologies can see some details inside the images, while human might not be able to see.

A computer interpreter can efficiently and consistently read many images, while human might make inconsistent assessments in an in efficient manner. Therefore, Computer Aided-Detection (CAD) and Computer Aided Diagnosis (CADx) become more desirable and are now under development by many research groups in the world. Computer aided disease diagnosis proven to be very helpful and many systems where used to help in the diagnosis of many diseases: Lung cancer-currently, radiologist can fail to detect lung nodules in up to 30 percent of actually positive cases.

Manuscript Received on November 2014.

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If a computerized scheme could alert the radiologist to locations of suspected nodules, then potentially the number of missed nodules could be reduced. Furthermore the evaluation of different use interstitial disease is one of the most difficult problems in diagnostic radiology. A thoracic CT scan generates about 240 section images for radiologists to interpret (Acharya and Ray, 2005)

Chest radiography-computerized automated analysis of heart sizes; an automated method is being developed for determining a number of parameters related to the size and shape of the heart and of the lung in chest radiographs (60 chest radio- graphs were generally acceptable to radiologist for the estimation of the size and area of the heart project. Colon cancer-colon cancer is the second leading cause of cancer deaths for men and woman in the USA. Most colon cancers can be prevented if recursor colonic polyps are detected and removed. CT colonography (virtual colonoscopy) is being examined as a potential screening device (400-700 images) (Acharya and Ray, 2005).

Artificial Neural Network Computer-Aided Diagnosis (ANNCAD) scheme for the diagnosis of Alzheimer's disease with multi centre data using the registration and region based statistics. In this study we developed a new algorithm that can be used to detect the deformation in abnormal skins texture and color due to infection and to recognize skins that have a specific disease form those with other diseases. The disease we chosen is psoriasis. Many skin recognition and modeling methods depends on skin color (Hwei-Jen et al., 2005) which have many difficulties. The skin color depends on human race and on lighting conditions, although this can be avoided in some ways using YCbCr color spaces in which the two components Cb and Cr depend only on chrominance, there still many problems with this method because there are many objects in the real world that have a chrominance in the range of the human skin which may be wrongly considered as skin. Also many skin diseases will cause deformation in skins texture as well as the color. For the above reasons combining the texture features of skin with its color feature will increase the accuracy of skin disease diagnosis systems.

II. PSORIASIS

Psoriasis is a common skin condition that changes the life cycle of skin cells. Psoriasis causes cells to build up rapidly on the surface of the skin. The extra skin cells form thick, silvery scales and itchy, dry, red patches that are sometimes painful. Psoriasis is a persistent, long-lasting (chronic) disease. There may be times when your psoriasis symptoms get better alternating with times your psoriasis worsens. The primary goal of treatment is to stop the skin cells from growing so quickly. While there isn't a cure, psoriasis treatments may offer significant relief. Lifestyle measures, such as using a nonprescription cortisone cream and exposing your skin to

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small amounts of natural sunlight, also may improve your psoriasis symptoms.

A. Types of Psoriasis:

Part of understanding and managing your condition is working out what type of psoriasis you have and what might lead to flare-ups. Together with support from your doctor, family and friends, this will help you to manage your condition. You may not be affected in the same way as someone else with psoriasis, so it is about getting to know your body and how it reacts in certain situations.

The type of psoriasis you have can be worked out by looking at where it appears on your body, severity and appearance of affected patches of your skin. The most common type of psoriasis is plaque psoriasis, affecting around 80% of people with the disease. Some people may have more than one type of psoriasis. For much of the public, psoriasis is an uncomfortable, unsightly skin condition. However, for those with psoriasis, it means an often painful and intensely itchy chronic autoimmune disease that appears on the skin. According to the National Psoriasis Foundation, psoriasis is the most common autoimmune disorder in the United States, affecting up to 7.5 million people (NPF, 2012). There are five official types of psoriasis: plaque, guttate, inverse, pustular, and erythrodermic, psoriasis. There are also subcategories of psoriasis types, which appear differently depending on where it is located on the body. See what they look like by viewing the pictures in this educational slideshow.

a) Plaque Psoriasis: Plaque psoriasis is the most common form of psoriasis, affecting 80 percent of people with psoriasis (NPF, 2012). It often appears on the elbows, knees, lower back, and scalp. It is characterized by thick red patches of skin, often with a silver or white layer of scale (Fig.1). Some people inherit genes linked to psoriasis, but most develop the condition suddenly due to a number of psoriasis triggers. There is no single cause or cure for psoriasis. They are often itchy and painful, and they can crack and bleed.

If you develop a rash that doesn't go away with an over-the-counter medication, you should consider contacting your doctor. Your doctor will look for raised, red scales with well-defined edges, and will consider how the rash responds to medication before making a diagnosis. Plaque psoriasis is most often found on the outside of knees and elbows, the scalp, the lower back, the face, the palms and soles of feet. When biopsied, psoriasis skin looks thicker and inflamed when compared with eczema.

b) ***Guttate Psoriasis:*** Guttate psoriasis appears in small red spots on the skin. It is the second most common form of psoriasis. The spots often appear on the torso and limbs, but they can also occur on the face and scalp. They are usually not as thick as plaque psoriasis, but they may develop into plaque psoriasis over time. According to the National Institutes of Health, this form of psoriasis often occurs during childhood or young adulthood, often after a “trigger” of strep throat, stress, skin injury, infection, or taking medication (NIH, 2011).

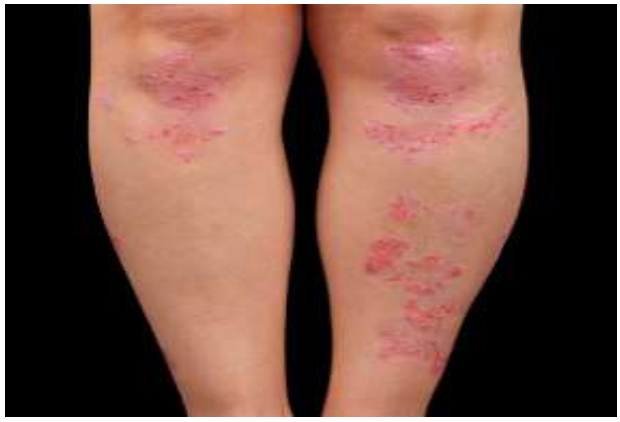

Fig. 1. Plaque Psoriasis

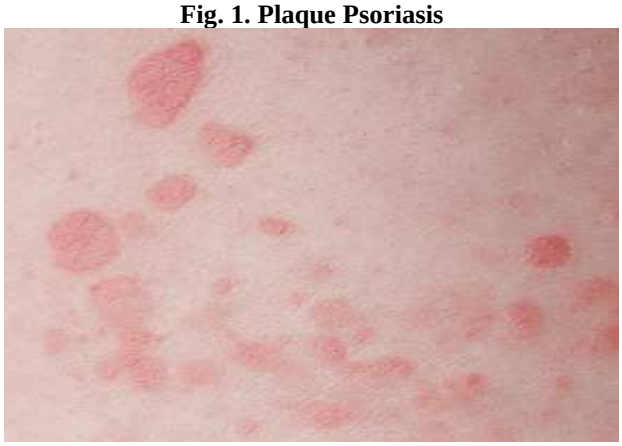

Fig.2. Guttate Psoriasis

This form of psoriasis appears as small, red, separate spots on the skin. Guttate lesions usually appear on the trunk and limbs and can number in the hundreds. Sometimes lesions form on the scalp, face and ears (Fig.2). They usually are not as thick as the lesions that characterize plaque psoriasis. This form can precede or co-exist with other forms of psoriasis, such as plaque. Known Triggers Guttate psoriasis often comes on quite suddenly.

c) ***Flexural or Inverse Psoriasis:*** Flexural or inverse psoriasis often appears in skin folds (under the breasts, in the armpits, or in the groin area). It is very red and often shiny and smooth. Most people with inverse psoriasis also have a different form of psoriasis in other places on the body (Fig.3).

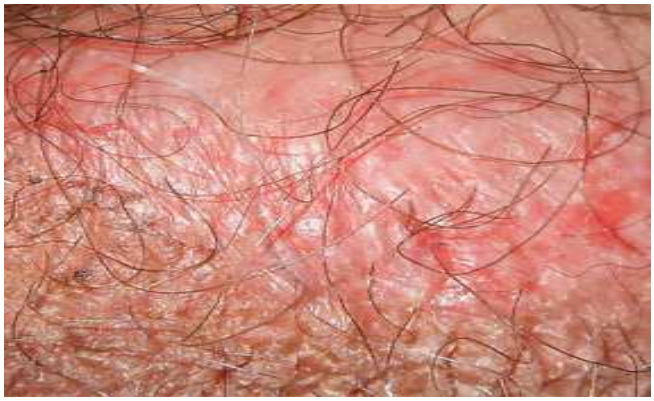

Fig.3. Inverse Psoriasis

The sweat and moisture from skin folds keeps this form of psoriasis from shedding skin scales, and the skin-on-skin contact can make inverse psoriasis very irritating. A variety of topical treatments are available and effective for inverse

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psoriasis. Inverse psoriasis (also known as intertriginous psoriasis) shows up as very red lesions in body folds. It may appear smooth and shiny. Many people have another type of psoriasis elsewhere on the body at the same time.

Inverse psoriasis is found in the armpits, groin, under the breasts and in other skin folds on the body. It is particularly subject to irritation from rubbing and sweating because of its location in skin folds and tender areas. It usually lacks the scale associated with plaque psoriasis due to the moist environment. It is more common in overweight people and people with deep skin folds.

d) ***Pustular Psoriasis:*** Pustular psoriasis is characterized by white pustules surrounded by red skin. The pus inside the blisters is noninfectious. Scaling also occurs. There are three kinds of pustular psoriasis: von Zumbusch, palmoplantar pustulosis (PPP), and acropustulosis. Each of the three forms of this type of psoriasis has different symptoms and severity. Pustular psoriasis may affect isolated areas of the body, like the hands and feet, or cover most of the skin's surface. Some people experience cyclic periods of pustules and remission. Pus-filled blisters require medical attention.

Pustular [PUHS-choo-lar] psoriasis in characterized by white pustules (blisters of noninfectious pus) surrounded by red skin. The pus consists of white blood cells. It is not an infection, nor is it contagious (Fig.4)

Pustular psoriasis is primarily seen in adults. It may be limited to certain areas of the body — for example, the hands and feet. Generalized pustular psoriasis also can cover most of the body. It tends to go in a cycle with reddening of the skin followed by pustules and scaling. Computer technologies can make somewhat simple abnormality detection and disease diagnosis from the images, but could not replace the human ability to analyze complex information. On the other hand, computer technologies can see some details inside the images, while human might not be able to see.

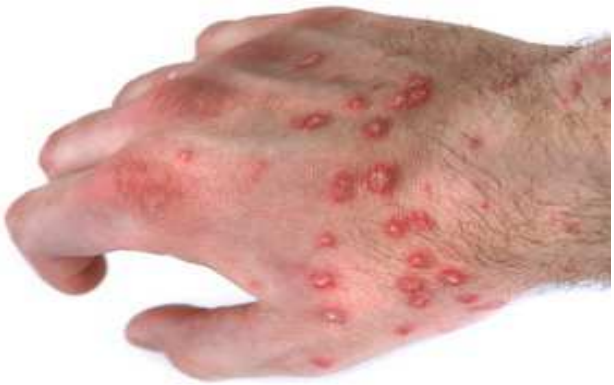

Fig.4. Pustular Psoriasis

e) ***Erythrodermic Psoriasis:*** According to the National Psoriasis Foundation, erythrodermic psoriasis is the rarest form of psoriasis, and it is very serious (NPF, 2012). This form of psoriasis looks like severe burns to the skin. It may cover large portions of the body, and exfoliation often occurs in larger pieces than the small scales typical to most psoriasis (Fig.5). It is very painful and may require hospitalization. Erythrodermic psoriasis can occur with Pustular psoriasis or develop from widespread, poorly controlled plaque psoriasis. It can also be caused by a bad sunburn, infection, alcoholism, significant stress, or abrupt discontinuation of a systemic psoriasis medicine. σ θ of psoriasis. Erythrodermic [eh-REETH-ro-der-mik] psoriasis is a particularly inflammatory form of psoriasis that often affects most of the body surface. It may occur in association with von Zumbusch pustular psoriasis. It is a rare type of psoriasis, occurring once or more during the lifetime of 3 percent of people who have psoriasis. It generally appears on people who have unstable plaque psoriasis. This means the lesions are not clearly defined. Widespread, fiery redness and exfoliation of the skin characterize this form. Severe itching and pain often accompanies it. Individuals having an erythrodermic psoriasis flare should see a doctor immediately. This form of psoriasis can be life-threatening.

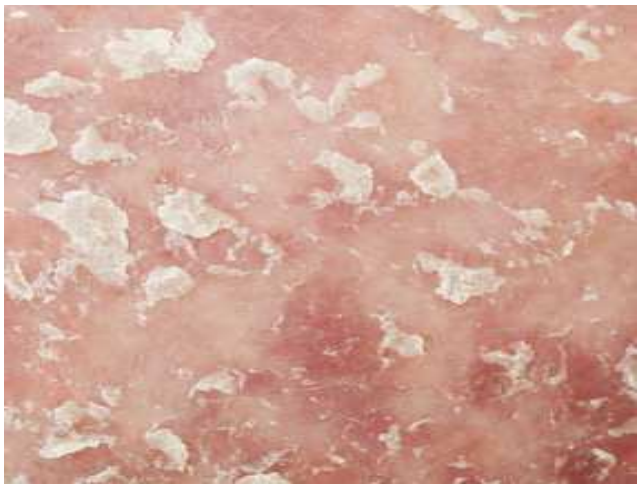

Fig.5. Erythrodermic Psoriasis

III. FEATURE EXTRACTION

Color features (color moment): Color moment is a compact representation of the color feature to characterize a color image. It has been shown that most of the color distribution information is captured by the three low-order moments. The Ist-order moment (μ_c) captures the mean color, the second-order moment (σ_c) captures the standard deviation and the third-order moment captures the skewness (θ_c) of color. These three low-order moments (μ_c, σ_c, θ_c) are extracted for each of the three color planes (R G B), using the following mathematical formulation:

$$\mu_c = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} p_{ij}^{c} \qquad (1)$$

$$\sigma_c = \left[\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(p_{ij}^{c}-\mu_c)^2\right]^{1/2} \qquad (2)$$

$$\theta_c = \left[\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(p_{ij}^{c}-\mu_c)^3\right]^{1/3} \qquad (3)$$

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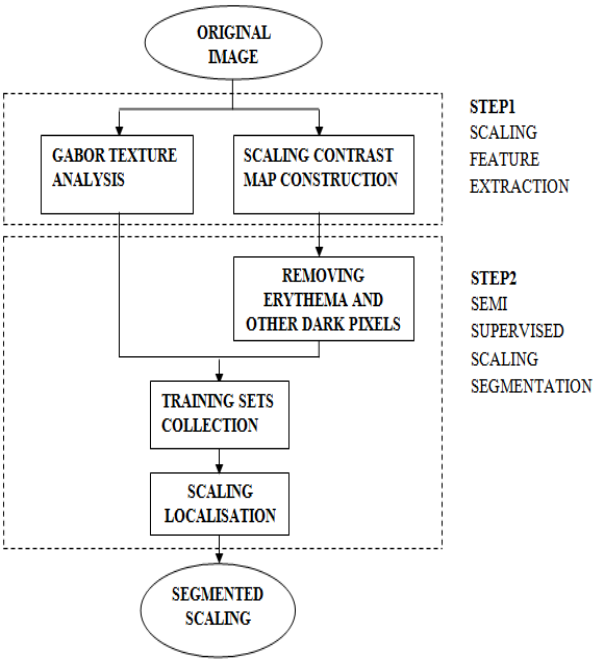

Fig.6. Proposed System Block Diagram

Proposed block diagram composed of two main stages: 1) A feature extraction stage and 2) A scaling segmentation stage. The two stages are described as follows (Fig.6).

Step 1) The algorithm first analyzes skin color and skin texture using an appropriately chosen color space and bank of Gabor filters to create a feature space for the image.

Step 2) The algorithm next removes erythema pixels from consideration and resample's the image to collect training samples for the classification process. The segmentation is achieved by using a MRF and the hyper plane derived from a support vector machine (SVM).

Above two steps are broadly described into 5 steps:

1) Preprocessing:

Preprocessing is removal of noise contents present in the image. We using the preprocessing algorithm are 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.

2) ***Feature extraction:***

Feature extraction is extracting the number of important objects present in the image. Algorithm of extraction is Gabor Texture analysis

The algorithm uses a bank of 24 Gabor filters designed to respond well in a variety of skin and scaling texture conditions. Finally, the Gabor texture image is acquired by summing the smoothed output over all of the rotation angles and frequencies of the Gabor filters. The summation in the final step preserves the differences between the higher response from scaling and the lower response from normal skin.

3) Removing erythema:

Threshold out the dark pixels representing erythema, hair, moles and other blemishes are removed using the scaling contrast map.

4) Training sets collection and localization:

- The training set constitutes of pixels that are highly likely to be scaling and pixels that are highly likely to be normal skin.
- Training data is gathered 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.
- An Approximate Localization of Erythema
- Obtaining a Sample of Scaling and Skin Pixels
- Soft-Constrained K -Means Clustering

5) Segmentation:

Segmentation of scaling from normal skin using SVM and MRF algorithms. SVM is 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. SCALING CONTRAST MAP:

Pre-processing is removal of noise contents present in the image. We using the pre-processing algorithm are 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 centre-surround filters that increase the contrast between scaling and erythema.

B. GABOR FILTER:

In image processing, a Gabor filter, named after Dennis Gabor, is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. The Gabor filters are self-similar: all filters can be generated from one mother wavelet by dilation and rotation.

Gabor filters are directly related to Gabor wavelets, since they can be designed for a number of dilations and rotations. However, in general, expansion is not applied for Gabor wavelets, since this requires computation of bi-orthogonal wavelets, which may be very time-consuming. Therefore, usually, a filter bank consisting of Gabor filters with various scales and rotations is created. The filters are convolved with the signal, resulting in a so-called Gabor space. This process is closely related to processes in the primary visual cortex. Jones and Palmer showed that the real part of the complex Gabor function is a good fit to the receptive field weight functions found in simple cells in a cat's striate cortex.

The Gabor space is very useful in image processing applications such as optical character recognition, iris recognition and fingerprint recognition. Relations between activations for a specific spatial location are very distinctive between objects in an image. Furthermore, important activations can be extracted from the Gabor space in order to create a sparse object representation.

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Among various wavelet bases, Gabor functions provide the optimal resolution in both the time (spatial) and frequency domains, and the Gabor wavelet transform seems to be the optimal basis to extract local features for several reasons.

C. K-MEANS CLUSTEERING:

The algorithm uses a soft-constrained K-means clustering to select training data from the candidate sets $L_{scaling}$ and L_{skin} . The constraints are defined as the probability of data being in each cluster in the initial stage. We can see that the soft-constrained -means localized many more training samples than either the -means or the Fuzzy C means. Moreover, the soft-constrained -means is more robust to changes in skin color. When the skin is not evenly illuminated, the clusters obtained with the -means and the Fuzzy -means do not correspond well to the scaling and skin pixels in the image. When the skin color is similar to the scaling color, the centroids initially identified are swapped by the Fuzzy -means algorithm because of the effect of its membership function. Performance of the three clustering methods is analyzed statistically using Mean Absolute Difference (MAD) and Spatial Support (SS). We require that the training samples should be consistent with scaling and skin pixels in the actual image.

D. SVM WITH MRF:

SVM is 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.

SVMs are common technique for solving classification problems. The aim for the basic SVM is to find a hyper plane that separates a data set into one of two predefined classes. The hyper plane is defined using training data to estimate the hyper plane parameters so that the distance to any training sample is maximized .If a hyper plane 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. 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. 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 neighbourhood 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.

IV. EXPERIMENTAL RESULTS

A part of the clustering results is presented in Fig. 7. We can see that the soft-constrained -means localized many more training samples than either the -means or the Fuzzy C means. Moreover, the soft-constrained K-means is more robust to changes in skin color. When the skin is not evenly illuminated, the clusters obtained with the K-means and the Fuzzy -means do not correspond well to the scaling and skin pixels in the image. When the skin color is similar to the scaling color, the centroids initially identified are swapped by the Fuzzy K-means algorithm because of the effect of its membership function. The results from our method are compared with the traditional SVM and the MRF.

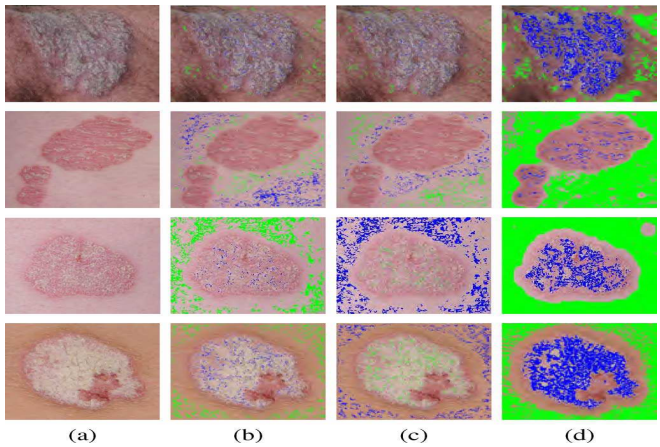

Fig. 7. Clustering results. Training samples for scaling are marked in blue and training samples for skin are marked in green. (a) Original image. (b) Training sets from the -means. (c) Training sets from the Fuzzy -means. (d) Training sets from the soft-constrained -means.

Inverse psoriasis (also known as intertriginous psoriasis) shows up as very red lesions in body folds. It may appear smooth and shiny.

Segmentation of scaling from normal skin using SVM and MRF algorithms. SVM is to provide an initial classifier that the MRF then uses to smooth the region located by the SVM.

According to the National Psoriasis Foundation, erythrodermic psoriasis is the rarest form of psoriasis, and it is very serious (NPF, 2012). This form of psoriasis looks like severe burns to the skin.

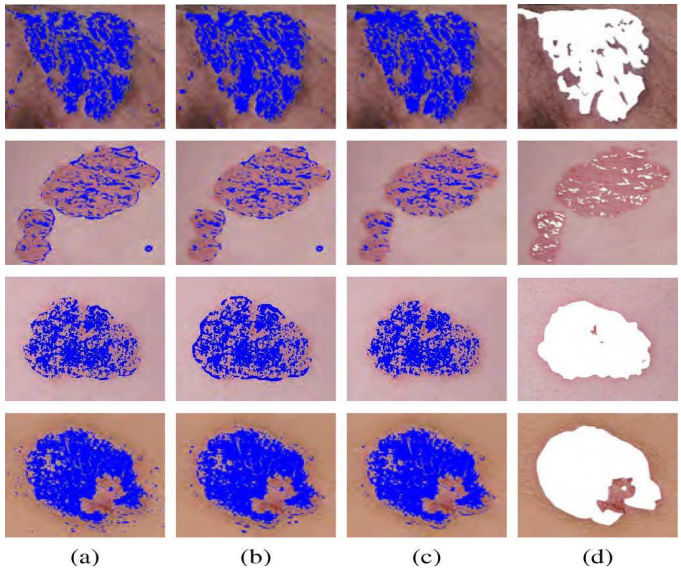

Fig. 8. Classification results of the original images in Fig. 7 with training sets from the soft-constrained -means.Detected scaling ismarked in blue. (a) SVM segmentation. (b) MRF segmentation. (c) Our segmentation. (d) Ground truth.

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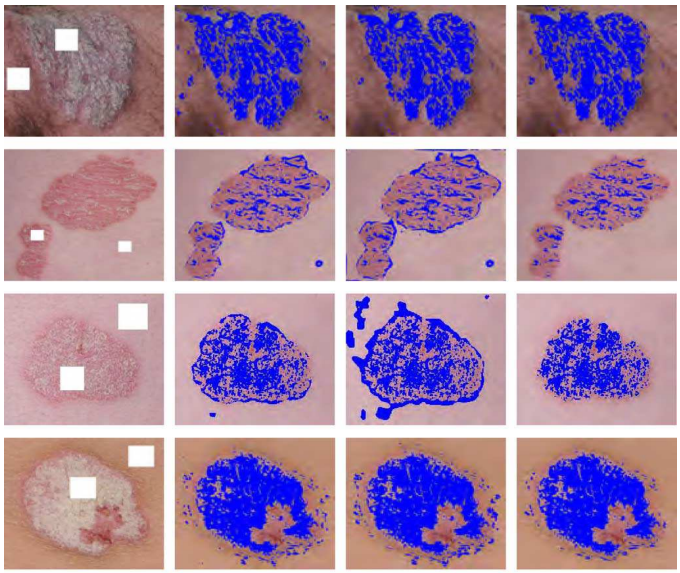
Some examples of the segmentation of scaling are shown in Fig. 8. The images indicate that our segmentation results are good at differentiating normal skin from scaling when there is normal skin around psoriatic lesions.



(a) (b) (c) (d)

Fig. 9. Classification results of the original images in Fig. 7 with manually selected training sets. Detected scaling is marked in blue. (a) Selected training sets marked with white. (b) SVM segmentation. (c)MRF segmentation. (d) Our segmentation.

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