



Efficient Detection and Classification of Diabetic Foot Ulcer Tissue using PSO Technique

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Abstract

Assessment of a diabetic wound is very much important to determine the healing status. Foot ulcer is most commonly observed problem of diabetic patients. A diabetic wound is observed for approximately 15 per cent of diabetic patients. Diabetic wound is a major concern of diabetes mellitus. The foot ulcer is the very much harm full problem related to diabetes mellitus. Here particle swarm optimization (PSO) based optimization technique is used for segmentation of diabetic wounds and classifying into three types of tissues i.e. granulation, necrotic and slough. After the segmentation the different textural features are extracted through Gray Level Co-occurrence Matrix (GLCM). All these features were then fed to two different classifiers, Naive bayes and Hoeffding tree for classifying the tissue types. The experimental results showed that the classification accuracy, sensitivity, specificity are 90.90%, 100%, 87.5% by Naive bayes, and 81.81%, 100%, 77.7% by Hoeffding tree respectively. Hence the PSO optimization techniques along with Naive bayes classifier could be used for the effective segmentation of diabetic wound images.

Keywords: Diabetic wound, PSO, GLCM, Textural features, Naive Bayes, Hoeffding tree.

1. Introduction

Segmentation of foot ulcer is a primary element in the image analysis that gives the basis for the further processes of treatment. The proposed algorithm is efficient to segment the wound area in a wide range of wound images. Varunkumar C. has proposed a technique which serves the purpose of true border extraction in the domain of dermoscopy relevant to skin images effected by wounds. This proposal has been identified as an efficient mechanism in the area of image segmentation [1]. Solis-Sanchez et al. [2] has proposed an advanced object segmentation technique with the intention of identifying and evaluating foot injury using computer vision for diabetic patients. They applied regional minimum watershed transformation algorithm for segmentation. Wang et al. [3] has proposed a new methodology for implementation of system based analysis in the area of novel based wound images applied on smart phones with android operating system. They are using mean shift algorithm for segmentation. Vilcahuaman et al. [4] has developed a process for optimized way to observe diabetic foot hyperthermia by infrared imaging. Here a Concrete method is developed in the area of image analysis for thermal images leading to acquisition of wound images. The supervised learning methods successfully used to detect and classify the type of wound tissues. Fast Fuzzy C-means and K-means techniques are used to form the cluster for classification and detection of boundary in wound images. The same technique is adopted for measurement of wound image sizes. They stated that the enhanced Fast Fuzzy C-means provides better visual segmented output compared K-means process in terms of high PSNR and low MSE values [5]. The wound image analysis using the Matlab application in the Android smartphone has been implemented successfully.

Smartphones are used to capture wound images and further processing is done with Matlab. Further the process of wound segmentation is followed by the application of accelerated mean shift algorithm. The overview of foot boundary is confirmed with respect to skin color and wound boundaries by applying a simple region growing segmentation technique. They recommended a PSO for modifying the enhancement feature CLAHE which is based on LCM [7]. Bhelonde et al. [8] has proposed a method to segment the wound in android phones by implementing accelerated mean shift algorithm. A wound image analysis system was implemented on the entire system, where the wound image presented in the system first and then, the segmentation of wound is done by the accelerated mean-shift algorithm [9]. Wannous et al. [10] stated that Wound assessments for varying lighting conditions and viewpoints may differ significantly across various examinations performed on the patients. Ait-Aoudia et al. [11] stated that they focus on providing solutions for optimizing problems using PSO methods. The quality of segmentation is measured using kappa index. This yields to results showing HMRF-PSO method more effective in comparison with K-means and threshold based methods. A novel method, A novel method provides a technique to apply segmentation on fuzzy filtered images. This technique is dependent on fuzzy rules in order to filter and make region based detections in images for instance on edges, homogeneous and noisy regions using various gradient filters and fuzzy membership rules. This method is further tested on various imaging modalities like ultra sound images and leads to efficient results that demonstrates its effectiveness [12]. Mohan et al. [13] Has recommended a PSO for modifying the enhancement feature CLAHE (Contrast Limited Adaptive Histogram Enhancement) which is based on LCM. is proposed. The main outcome of this paper was focused on improving accuracy levels of segmentation

and assessment of diabetic wounds by adopting improved watershed segmentation by flooding and pruning techniques [14]. Patel et al. [15] focused mainly in the area of recognizing and classifying foot ulcer wound detections. This work is based on classification techniques like support vector machine, fuzzy logic, K-nearest neighbor classifier. Sivayamini et al. [17] proposed a recommended techniques to compare search optimization techniques with PSO results. This work involves critical techniques like Cuckoo search optimization which is used to detect foot ulcers on thermography images. The status of wound healing is identified based on the combination of different color evaluation models such as yellow-black [19]. Filko et al. [20] Continuously worked on developing a model which helps in detecting and reconstructing and also segmentation of chronic wounds. This work is based on per block classification of wound tissues by applying color histograms and nearest neighbor techniques. In this paper, we have used PSO technique for efficient segmentation of the diabetic wound images. Different textural features are extracted using GLCM and used as input to the classifier to classify three types of diabetic wounds. The performance evaluation is done by calculating sensitivity, specificity, and accuracy.

2. Methodology

Diabetic wound images are collected from the open source database. The color segmentation is done through Particle Swarm Optimization (PSO) technique. The Region Of Interest (ROI) is extracted from the segmented image, different textural and colour based features are extracted and classified into three types of diabetic wound images using two classifiers namely Navie Bayes and Hoeffding tree classifier. Fig.1 shows the system overview of the proposed method to segment the diabetic wounds.

A. Particle Swarm Optimization (PSO)

Particle swarm optimization(PSO) is one of the most recent and rising digital image segmentation technique inspired from the nature. Kenney and Eberhart developed this technique in 1995. PSO is a computational method that optimizes a problem by step by step. The movement of each particle is affected by its local best known position. It's a population-based stochastic process which solves the continuous and discrete optimization problems.

Using the two best values the PSO is updated

p_{best} : In the solution space each particle coordinates are kept in track where they are associated with the best solution that has achieved by that particle. The value obtained is called personal best, p_{best} .

g_{best} : It is tracked by the PSO is the best value obtained so far by any particle in the neighbourhood of that particle. This value is called Global Best, g_{best} [6].

Following steps indicate the PSO segmentation technique:

Step1: The initial position and velocity of the different particles are specified indiscriminately according to the predefined ranges.

Step2: when each iterations are performed, all the particle velocities are amended as per the equation.

$$\vec{v}_i = w\vec{v}_i + c_1 R_1(\vec{p}_{i,best} - \vec{p}_i) + c_2 R_2(\vec{g}_{i,best} - \vec{p}_i) \quad (1)$$

Where \vec{v}_i and \vec{p}_i are the velocity of the particle and position of particle I. $\vec{p}_{i,best}$ and $\vec{g}_{i,best}$ are the positions which provides 'best' intended value discovered by the particle and the entire population of i respectively. The convergence behavior of PSO is controlled by w . In the range of 0 to 1 R_1 and R_2 are known as the random variables, c_1 and c_2 controls, how long a particle can move in only one iteration. Then the velocity of the particle is to be checked and then they are secured with the specified pre defined value to overcome the random violent walking of particles.

Step3: when a unit time interval is assumed between succeeding iterations, all the different particles positions are upgraded as per the given equation.

$$\vec{p}_i = \vec{p}_i + \vec{v}_i \quad (2)$$

\vec{p}_i will be then checked and are limited to the designated range.

Step 4: When the conditions are satisfied promote $\vec{p}_{i,best}$ and $\vec{g}_{i,best}$

$$\vec{p}_{i,best} = \vec{p}_i \text{ if } f(\vec{p}_i) > f(\vec{p}_{i,best}) \quad (3)$$

$$\vec{g}_{i,best} = \vec{g}_i \text{ if } f(\vec{g}_i) > f(\vec{g}_{i,best}) \quad (4)$$

Step 5: step2 to step4 will be repeated when a predefined number of iterations are not satisfied or when there is no progress for certain number of iterations. When the value is terminated, the algorithm describes the value \vec{g}_{best} and $f(\vec{g}_{best})$ as its solution. Fig. 2 describes the flow chart of PSO algorithm.

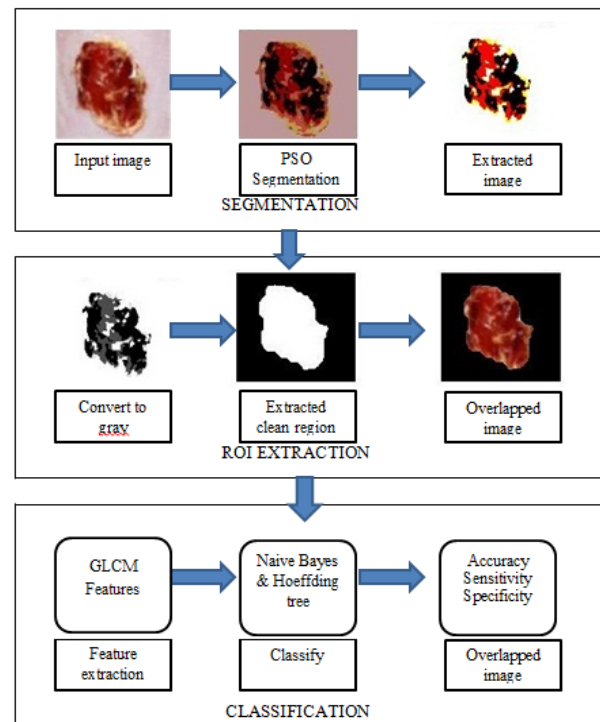


Fig. 1: The overview of the proposed system in segmenting the diabetic wound lesions

The PSO algorithm applied to the segmentation is arranged as follows

Step1: Segmenting image should be read.

Step2: Particular threshold level for PSO method should be selected.

Step3: Promote the particle fitness in the search space and update particle best in the search space.

Step4: If the swarm keeps getting better then reward the swarm or continue the swarm.

Step5: If the swarm has not improved its performance then remove the swarm or limit the swarm life.

Step6: continue the swarm as to spawn.

Step7: Delete 'failed' swarms and Reset threshold counter.

B. Feature Extraction

It is a technique where the characteristic attributes of an image is extracted. Here the textural features are extracted using GLCM. GLCM is the popular texture analysis method which is used to

calculate image properties which is closely related to second-order statistics. The first pixel is the reference pixel and the second pixel is the neighbor pixel. The GLCM is computed based on two parameters, which are the relative distance d and their relative orientation φ . The characteristics of diabetic wound images computed from GLCMs are energy, entropy, correlation and contrast.

Energy: It measures the textural uniformity of an image. The larger value of energy indicates more homogeneous the image.

$$Energy = \sum_{i,j} I(i,j)^2 \quad (5)$$

Entropy: The randomness of an image is measured by entropy.

$$Entropy = \sum_{i,j} I(i,j) \log(i-j) \quad (6)$$

Correlation: It measures how correlated a pixel to its neighbourhood. It can also be described as a measure of linear dependencies among neighbouring pixels in an image.

$$Correlation = \sum_{i,j} \frac{I(i,j)(i-\mu_i)(j-\mu_j)}{\sigma_i \sigma_j} \quad (7)$$

where, $I(i,j)$ is the gray-level value for each pixel in the ROI, and $\mu_i \mu_j \sigma_i \sigma_j$ are means and standard deviations of $I(i,j)$.

Contrast: The spatial frequency of an image is measured by the contrast.

C. Classification

The extracted features are fed in to the classifier. In this paper Naive Bayes and Hoeffding tree classifiers are used to evaluate the performance.

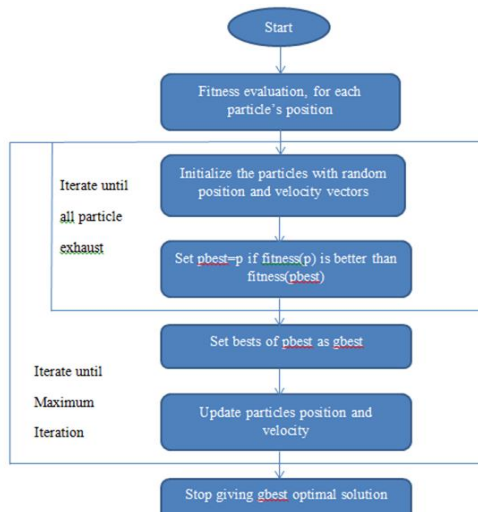


Fig. 2: PSO algorithm flow chart

Naive Bayes classifier

It is a simple and uncomplicated classifier based on Bayes theorem. It was used for classifying three types of tissue using texture features. If there are m classes C_1, C_2, \dots, C_m , whereas d dimensional feature space $X = (x_1, x_2, \dots, x_d)$ is considered as wound tissue descriptors. For a particular feature set X , classifier predicts the tissue type in one of the three classes where it achieves higher posterior probability; that is, granulation pixel belongs to the class C_1 if and only if $P(C_1|X) > P(C_j|X)$ for $1 \leq j \leq m, j \neq i$. Posterior probability is obtained using Bayes' theorem as

$$P(C_i|X) = \frac{P(X|C_i) \cdot P(C_i)}{P(X)} \quad (8)$$

where $P(C_i)$ denotes the prior probability and total probability is defined as

$$P(X) = \sum_{i=1}^m P(X|C_i)P(C_i) \quad (9)$$

Hoeffding tree classifier

It is a type of decision tree classifier. It is an incremental decision tree algorithm that is capable of learning from massive data streams. Hoeffding tree uses the Hoeffding bound for construction and analysis of the decision tree. Hoeffding bounds used to decide the number of instances to be run in order to achieve a certain level of confidence. Hoeffding bound states that with probability $1-\delta$, the true mean of the variable is at least $\bar{\delta}-\epsilon$. And ϵ is given by the following formula

$$\epsilon = \sqrt{\frac{R^2 \ln(\frac{1}{\delta})}{2n}} \quad (10)$$

D. Performance Evaluation

The parameters used to measure the performance of the classifiers are accuracy, sensitivity and specificity. Using True positive (TP), False positive (FP), True negative (TN) and False negative (FN) obtained from the confusion matrix of the classifiers the different parameters are measured. Accuracy measures the global performance of the classifier. Sensitivity measures the reliability of the system at making positive identifications and specificity measures the reliability of the system at making negative identifications. The following equations are used to evaluate the performance of the proposed method.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (11)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (12)$$

$$Specificity = \frac{TN}{FP+TN} \quad (13)$$

3. Results

The diabetic wound images are segmented using PSO technique. After that the ROI is extracted for feature extraction. The ROI is obtained by overlapping the original image with extracted clear region. Then the different textural features are extracted using GLCM. Then the extracted features are directly fed in to the classifier for the performance evaluation. Three diabetic images of various shapes and various categories namely granulation, necrotic and slough are collected from the open source and the PSO technique is used to segment these wounds. Fig. 3 shows the segmented images after the applying PSO techniques. The range of GLCM feature values obtained for diabetic wound images is shown in Table 1 and the performance evaluation of the classifiers are shown in Table 2. The proposed approach good classification accuracy of 90.9% in Naive bayes classifier, which is better than the result of Hoeffding tree classifier.

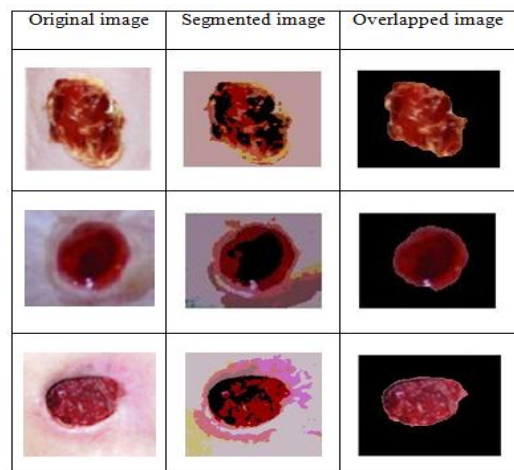


Fig. 3: Extracted the required ROI

Table 1: Range of feature values obtained for diabetic wound

| Features | Granulation | Necrotic | Slough |
|-------------|---------------------|--------------------|-----------------------|
| Energy | 0.971484 - 0.983503 | 0.968608-0.970294 | 0.958087 -0.962482 |
| Entropy | 0.183463 - 0.106522 | 0.217172-0.132835 | 0.128959- 0.114583 |
| Correlation | 0.177623 - 0.300919 | 0.133439- 0.175539 | 0.325179- 0.358565 |
| Contrast | 2.18716 - 1.828283 | 2.39940- 2.0753 | 1.747445- 1.589138 |

Table 2: Performance of the classifier for diabetic wound

| Parameters/classifiers | Naive bayes classifier (%) | Hoeffding tree classifier (%) |
|------------------------|----------------------------|-------------------------------|
| Accuracy | 90.9 | 81.8 |
| Sensitivity | 100% | 100% |
| Specificity | 87.5% | 77.7% |







| Input image | Tissue classified image | Percentage of tissue | Status |
|---|---|--|---------|
|  |  | G = 37.12% S = 12.23% N = 50.64% | Stage 3 |
|  |  | G = 46.08% S = 0.06% N = 53.85% | Stage 3 |
|  |  | G = 57.07% S = 0.34% N = 42.58% | Stage 2 |

Fig. 4: Types of wound tissue characterized pseudocolored pixels; representing % of Granulation (G), Slough(S), Necrotic(N) tissue pixels

Granulation: It is a type of tissue which is soft in nature and consists of red or dark pink colored tissues. The apparent shape is structured due to punctuate haemorrhages. If it is persisting healthy nature then it is experienced as painless. It also contributes in healing of wounds very effectively.

Slough: This tissue is having combined feature of white or light yellow colored tissue covering the peripheral layer of wound bed. Basically it is pertaining with string like structure hence it appears to be sticky with thick or thin pattern.

Necrotic: This type of tissue yields premature death of cells which appears to be dark brown or black colored. This nature results in delaying the wound healing process. Also it leads to some of the areas which are affected with lack of blood supply.

Based on the clinicians opinion by considering the percentage of granulation tissue the wound is divided in to four stages

Table 3. Stages based on percentages of granulation tissue

| Percentage of granulation tissue | Stage |
|----------------------------------|-----------------------|
| 100 – 75% | 1 st Stage |
| 74 – 50% | 2 nd Stage |
| 49 – 25% | 3 rd Stage |
| 24 – 1% | 4 th Stage |

4. Conclusion

In this paper, the PSO colour based segmentation is used to detect the boundary of the wound. Then the different textural features are extracted. Through GLCM we extract the textural features. Then these features are directly fed in to the classifier to evaluate the diabetic wound. There are two classifiers are used to evaluate the wounds. Both the classifiers are effectively classifies the wounds by using different textural features. The Naive Bayes classifier gives an accuracy of 90.90% and Hoeffding tree classifier gives an accuracy of 81.81%. The future scope mainly focuses on to improve the accuracy of tissue segmentation and classification for assessment of the wound healing status in diabetic.

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