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碩士論文

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Master Thesis

基於基因演算法及非監督式評估

傷口影像的切割與最佳化

Segmentation of wound image and optimization

based on genetic algorithm and unsupervised evaluation.

施學甫

Hsueh-Fu Shih

指導教授：賴飛羆 教授

Advisor: Feipei Lai, Ph.D.

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中文摘要

在病人接受手術之後，傷口的術後照護對病人的健康狀況佔了很重要的因素，往往都需要花費數日甚至數週的時間，在病房等待傷口穩定後才能出院，需要醫護人力來注意傷口四周的發炎感染跡象。

隨著影像辨識以及機器學習技術的演進，許多近來的研究提出了類似的解法，有透過大量資料透過卷積類神經網路進行學習，或者使用高解析度及紅外線攝影機進行精確攝影定位的傷口分析，但在我們的使用場景中，我們希望病人及醫護端使用者可以使用較少的資料運算資源以及不需高門檻的硬體設備，便能得到即時的傷口狀態評估。

本論文計畫開發一個演算法與系統使術後傷口的照護與發炎感染判斷能夠自動化，以統計及電腦視覺的方式來評估傷口是否有發生感染，並且與台大醫院遠距中心合作，整合台大醫院資訊系統，承接台大醫院–心臟節律器傷口自動判讀照護計畫，此研究計畫開發並改進傷口切割及判讀的演算法，使其更適用於目前的使用場景，建立傷口照護照片的雲端資料庫，建立對應行動裝置的 APP 以利病人及護理人員使用，並透過所接收的資料進行整體機器學習演算法的改良。

本篇論文著重於傷口影像的切割定位及其最佳化演算法，使用了基於灰階色彩空間強度進行動態閾值決定，以及引進不同的最佳化方法，包括基因演算法等來進行切割結果的最佳化，並提出了一個評估傷口切割效率的評估函數。透過與台大醫院外科部合作的手術傷口資訊進行驗證。

傷口切割定位演算法在台大醫院心臟外科部提供的心臟節律器傷口資料上

達到了 75.7%的準確度，透過基因演算法及評估函數的最佳化後更達到了 94.3%
的切割效率。

關鍵字 影像切割 電腦輔助診斷 最佳化 基因演算法 傷口判讀

Abstract

After the surgery being taken, the after care of the surgical wound has a great impact toward the patients' prognosis. It's often takes few days even few weeks for the wound to stabilize. It's is a great cost of health care and nursing resources.

The advance of image process and machine learning improves the accuracy of wound assessment and analysis and there are some recent works started on this field of wound analysis. In our tele-health scenario, we hope the user can use their mobile device to obtain a accurate result without using high-end camera.

In this literature we proposed an image segmentation algorithm based on edge detection and Hough transform. We further developed an optimization method based on unsupervised image segmentation evaluation and genetic algorithm.

The result was evaluated by the image provided by NTUH, division of surgery. We also implemented an analysis system cooperate with NTUH telehealth center, which has been used on pacemaker implantation patient.

The result of performing this segmentation algorithm on the data set provided by

NTUH, Division of cardiovascular surgery, achieve the accuracy of 75.7%, after the

optimization of genetic algorithm it achieves 94.3%.

Key word: Image segmentation, Computer Aided Diagnosis, Optimization, Genetic

algorithm, Wound analysis

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Chapter 1 Introduction

1.1 Introduction

Many patients are suffering from wound infection and chronic wounds, which cause a lot of annual spending in public health care [1]. While the majority of costs are attributed to hospital admissions and surgery, the majority of long-term care costs are attributed to home care. Computer aided diagnosis become a major trend of solving these kind of problems [2]. The telehealth center of National Taiwan University Hospital devote to reduce the expenditure and the cost of human power in variety of health care solution, including the development of automatic assessment of surgical wound. We try to provide a system enable patients to use their mobile device to obtain a preliminary assessment.

The advance of image process and machine learning improves the accuracy of wound assessment and analysis [2][3], and there are some recent works started on this field of wound segmentation and infection analysis [4]. Many studies achieved a high accuracy of wound analysis, which based on hand craft feature and trained by a large

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amount of high-resolution data. However, due to the feasibility of tele-healthcare and

the image capture device, we developed a non-learning based and low quality-needed

algorithm for wound image segmentation and an SVM-based low-data-quantity needed

wound analysis system.
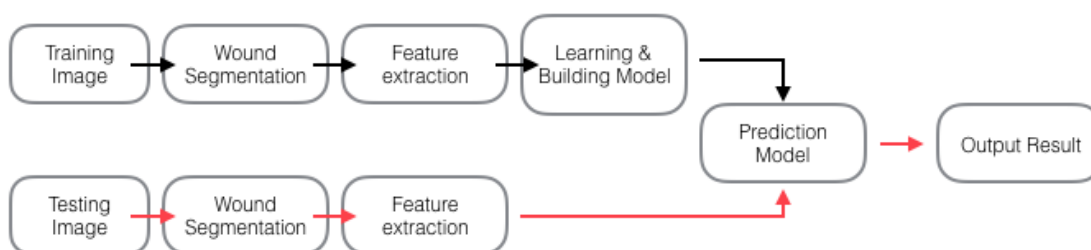
figure 1 Overview of our application system

This paper focuses on the development and optimization of wound segmentation

part and present a pipeline algorithm based on adaptive threshold on edge detection and

Genetic Algorithm optimized threshold.

1.2 Image Segmentation

Segmentation is an essential step in image processing, especially in our system, its

give the region of interest of the wound and provide a clean area for predictor to

analysis the wound condition with little information, so a clean and neat wound

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segmentation is important in extracting information.

Digital Image Processing, 3rd edition, R. C. Gonzalez and R. E. Woods, [5] categorized the segmentation method into three part, region based, data clustering and edge based segmentation. Over the years a wide range of thresholding techniques has been developed and considerable research continues nowadays. In our work, we focused on the edge-based segmentation method. This type of segmentation method generally applies edge detection operator or edge concept to segment the different region. The main objective of edge detection method is to adapt an operator to find the edge of image, and there are several studies working on deciding which edge is relevant to our interest segmentation region.[6]

Here we develop a robust-edge decision method based on the canny edge detector to decide whether the edge belongs to the ROI or not. The main idea is to dynamically decide the strong threshold of canny edge detector.   Based on this method we further developed a threshold-optimizing algorithm to achieve a higher accuracy in image segmentation.

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1.3 Genetic algorithm

To find the optimize threshold for edge detection and region thresholding, we need an optimization algorithm. There are several method [7][8] including Simulative Annealing, Gradient descent, PSO and Genetic algorithm. Here we adapt the genetic algorithm to solve this problem, the reason of using GA is 1. It is easy to implement. 2. We don't need a definite solution but a near optimal convergence. 3. There are several evaluation functions (Fitness) proved to be useful in image segmentation region evaluation.
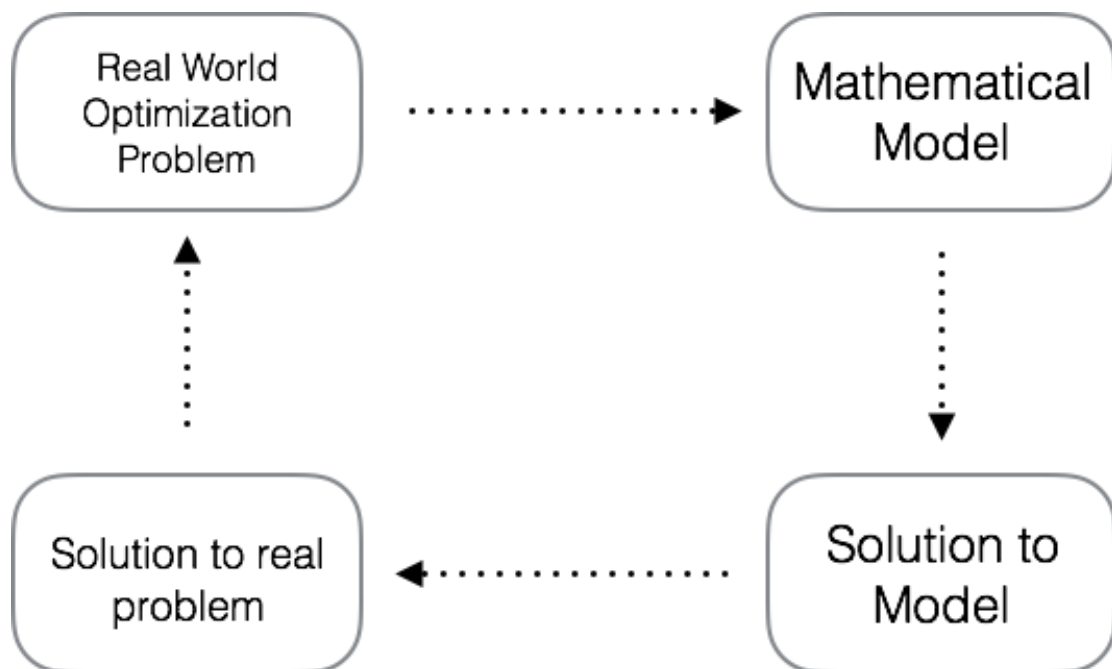

figure 2 Optimization process.

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GA is an efficient searching tool that was invented by John Holland[[9],although it doesn't guarantee the best possible solution, but it provide a optimal or partly optimal solution by approximation in a relatively short time. It is a powerful stochastic optimization method, which inspired by nature genetic behavior, providing a mathematical approach to model a real-world optimizing problem. By using a robust fitness function, it connects the real world problem to a mathematical model. The solution of the model is given by a algorithm using GA operators- Initialization, Selection, Crossover and Mutation, with the approaching of optimal solution to the mathematic model. By optimizing the fitness function and interpretation, it can project the solution from model to the real world problem. Further information and detail about GA will be described in Chapter2.

1.4 Unsupervised Segmentation Evaluation

As mentioned before, Image segmentation is a step to segment out the ROI, extensive research has been done in creating many different approaches and algorithms for image segmentation. But we need to define the "Interest" of the segmentation result.

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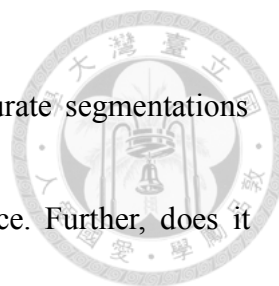
It is difficult to assess whether one algorithm produces more accurate segmentations than another, or more generally, a measurement of the performance. Further, does it segment out the region we need? Hence we have to evaluate the result of segmentation. Zhang et al. [10] classify the evaluation function into to categories, supervised and unsupervised.

Supervised   Answer =y'   Find the minimum $_{\Delta y}$

$$f_1(x) = y_1 \quad y' - y_1 = \Delta y_1$$
$$f_2(x) = y_2 \quad y' - y_2 = \Delta y_2$$

Unsupervised   Evaluation function G(x)   Find minimum z

$$f_1(x) = y_1 \quad G(y_1) = z_1$$
$$f_2(x) = y_2 \quad G(y_2) = z_2$$

figure 3 Supervised vs Unsupervised

Supervised method gives a ground truth to the segmentation result; it is trivial that we need an "answer" to the question, which is useful when it comes to the comparison of few segmentation algorithms. Which is also useful when doing a machine learning model, it can simultaneously feedback to the function and adjust the model parameter to find out the optimal function $f'(X)$.

On the other hand, unsupervised evaluation does not need the ground truth, it

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gives an evaluation function $y = G(x)$. If the function $G(x)$ is robust enough,

comparing the different y value can evaluate the performance of the algorithm, or in our

scenario, feed back to optimizing the threshold we need.

In order to autonomously select among few possible segmentations within a

segmentation algorithm or a broader application, we applied some unsupervised

evaluation function we found in some relate works [10][11][12]. Due to the criteria of

evaluation is often application-dependent; we work on finding some partial optimal

solution to this problem.

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Chapter 2 Method

2.1 Segmentation Algorithm Pipeline

Robust-Edge Detection · → Skin Region Detection · → Wound Reconstruction

figure 4 Overview of segmentation algorithm

Our algorithm based on few observations. 1. Skin region pixels are in certain value of color space, 2. Wound region are the most robust edge area in the skin region. By this two fact, we developed a system, which can divide into three parts, robust-edge decision, skin region detection and reconstruction of the wound region. To redeem the bias of environment and the image capture device, we also perform a color normalization based on the pixel value near the robust edge region in order to normalize the color value of skin.

First step is robust-edge detection. We calculate the robustness of each edge detected by the canny edge detector, to decide the best strong threshold for the canny operator. Canny operator consists of a Gaussian filter, Non-maxima suppression and

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hysteria threshold. Hysteria threshold means there were 2 thresholds adapted to decide a

pixel to be strong, weak or candidate, strong pixel is the threshold we want while the

weak one isn't. The candidate threshold than calculate the orientation of the threshold to

be parallel or across the strong edge for the further decision. By choosing the optimal

threshold by calculating the mean gray scale value of separate region create by the edge,

we can optimize the hysteria threshold, and obtain the strongest edge we need by this

algorithm.

Some wound region might be tattered, so it is important to reconnect the edge and

create a more robust edge if necessary. The connection of edge is performed by

connected component labeling and optimized by mean gray pixel value. The edge of the

edge detected by the canny operator will perform this algorithm and decide the
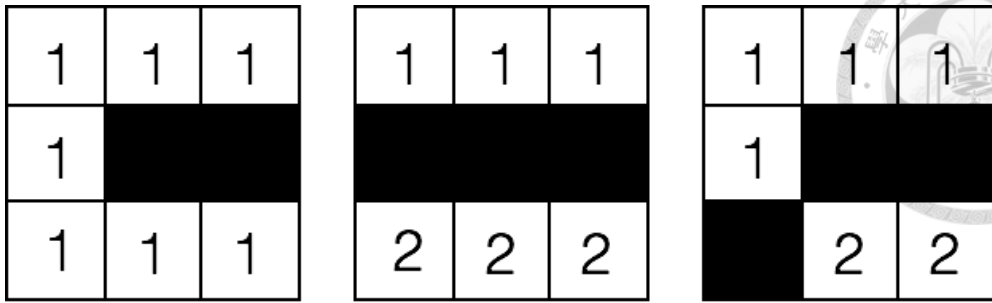
connected pixel is needed or not.

figure 5 Edge decision algorithm

$$Max \ (|\frac{\sum P_1}{N1} - \frac{\sum P_2}{N2}|)$$

Till now, we can obtain the optimal edge we need, but the strongest edge does not

equivalent to the wound, the edge with an exceed gray value might be a background

artifact (noise), the decision of this threshold will be optimized by the GA, which will
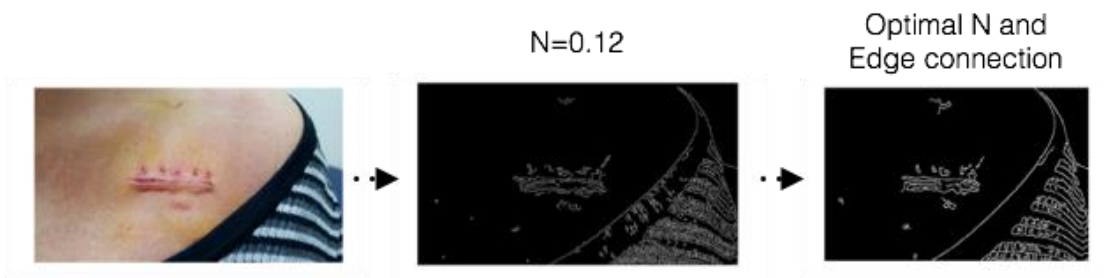
be described in the further section.

figure 6 Adaptive threshold of robust edge detection

Second part of this algorithm is the detection of the skin region, normally the skin

can be decided by a skin color model, Alberto el al[14] proposed a threshold value of

skin model, there are a variety of color space, P. Kakumanu et al [15] compared the

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efficiency between different color spaces, and gives a result that HSV color space best suit for the skin color modeling. So we use HSV color space to perform a skin region decision model.

$$0.035 <= H <= 0.7$$

$$0.005 <= S <= 0.8$$

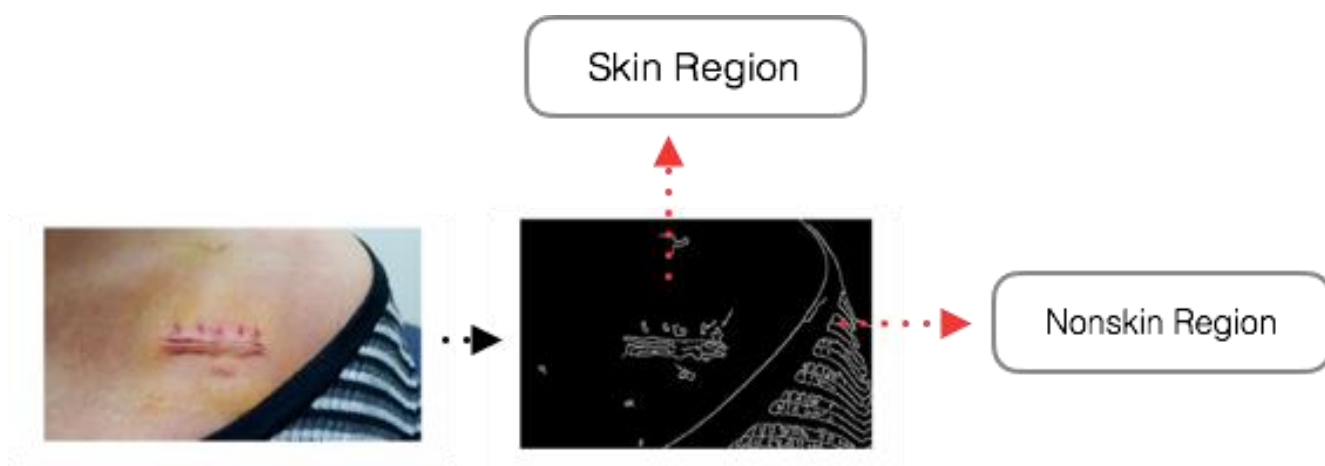$$0.35 <= V <= 0.9$$

figure 7 Decision of skin region

Further more, by the robust edge we obtain in the first step, we can decide if the edge is located in the region accord with the color model, and respectively, decide the skin region with a robust edge locate in. Due to the color of the wound varies, we can't simply exclude the pixel based on the color value, but also the region mean value and

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the location of robust edge.

figure 8 Decision of skin region(2)

By combining the two results we obtain in the last two steps, we can almost guarantee the skin region except some boundary condition. After we segment out the skin area, we can perform the color normalization step by the average of skin region pixel value and directly normalized the whole picture with the mean value.

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Color normalization

figure 9 Color normalization

The normalized image and the robust edge will than pass to the third step, the reconstruction of the wound region. It includes Hough transform to detect the wrinkle count of the segment region and some morphological process to reconstruct the wound.

By applying dilation and erosion operator, we can smooth the edge and connect the robust edge into a mask of wound.

Procedure:

Step1 Perform a large kernel smoothing on each robust edge. E_k K = 1,...,N.

Step2 Calculate the wrinkle near E_k by Skeleton operator and Hough transform.

Step3 Eliminate the edge with exceed color error

$$E_x = \{E_k \mid lower\ bound < P(E_k) < upper\ bound\}$$

Step4 Perform re-segment on the region with large wrinkle in E_x until it achieve certain wrinkle count.

Step5 Compare with the skin region.

Step6 Perform Skeleton and Endpoint operator and connect the outer point to reconstruct the wound region.

Hough transform is a projection method, which convert the line in an image with coordinate system xy to another coordinate, the point on the original line will draw a line in the new coordinate xy', and the cross point of the line in xy' represent the original line in the xy plane. By doing so we can detect the cross point in xy' plane to detect any shape which can be described in a equation including line, ellipse, circle, and

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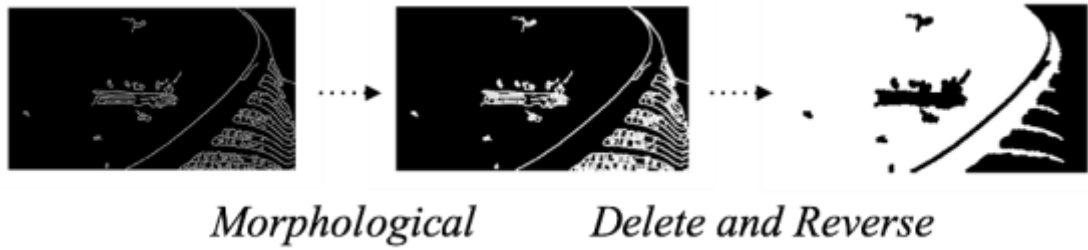rectangle. We use this transformation to detect the wrinkle of region near each robust

edge.

figure 10 wound reconstruction

figure 11 wound reconstruction 2

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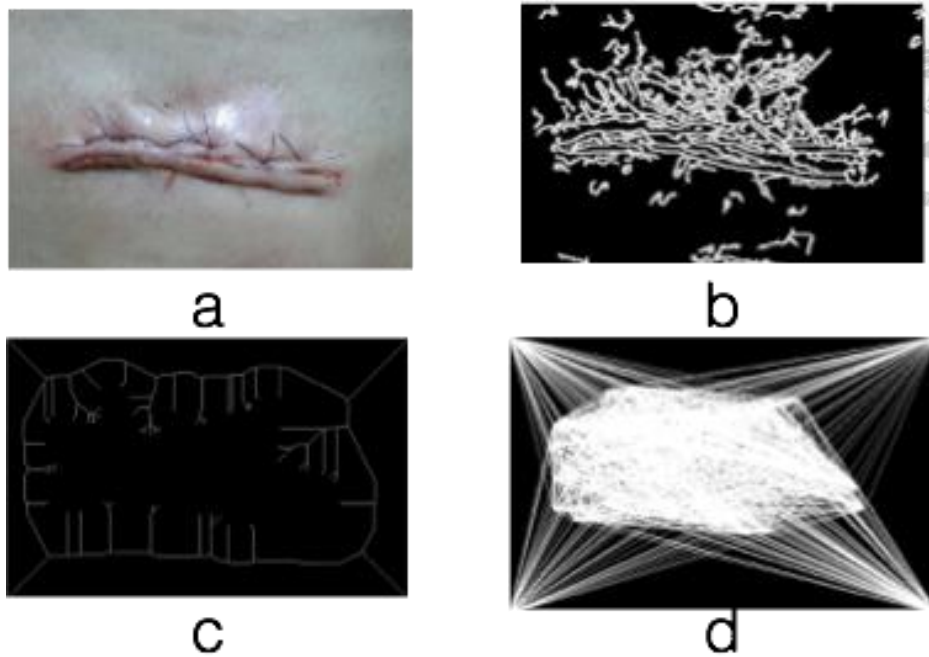
figure 12 wound reconstruction 3

a. Original wound image.

b. Optimal robust edge.

c. Skeleton of the mask.

d. Reconstruct of the wound region.

By these operators, we can segment the wound region with a satisficing accuracy while boundary condition and exception still exist. The following part is to autonomously optimize the threshold to detect noise and artifact of image by threshold.

2.2 Optimize the segmentation

As before mentioned, there exist some boundary condition and special cases that

background noise and artifact might exceed the robustness of the wound, if the pixel

color value also accord with the color model after we perform the normalize, we may

result in a false segmentation. To avoid this condition, we perform a threshold step.

$$Px = \{x|x_{xy}\}$$

$$P'x = Px - Dx\{x|Px > T| < T\}$$

Px is a set of whole image pixel, and $P'x$ is the exclusion of the pixel value

exceed or under certain threshold value, this threshold value can sometime be empirical,

but an autonomous decision is needed in order to solve these boundary condition.
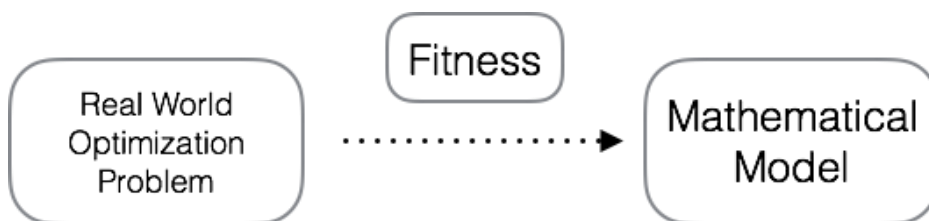

figure 13 Overview of optimization

To evaluate whether the threshold is acceptable or not, we need some evaluation

function to project the problem to the mathematical field. By choosing a fitness function,

we can equalize the real optimization problem with the mathematical model, once we

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solved the model, we can optimize the real problem.

In the introduction section we briefly explained why we need an unsupervised

evaluation. There are some previous study [10][11][17] about unsupervised method of

the segmentation measurement. Most of them are based on entropy. Some other

technique used gray level difference, mean value, *busyness*, and shape etc. The decision

of the function is often application-wise. Those functions have been divided into

numerous types including quantitative evaluation measures [17]

Here we introduce some functions and the explained why is it suitable to our

application. In Borsotti et al [17] they empirically proposed a quantitative evaluation

function Q(x).

$$Q(I) = \frac{1}{1000 \times Na} \sqrt{n} \sum_{j=1}^{n} \left[\frac{e_j^2}{1+\log L(R_j)} + \left(\frac{M(L(R_j))}{L(R_j)} \right) \right] \qquad \text{Eq 1}$$

I is the given image, Na is the number of pixels in I, n is the number of regions, Rj

means the jth region, L(Rj) is the number of pixels in jth region and ej is the color error

of jth region.

The first term of Q is a normalization factor and the second term penalizes results

with too many regions. The last term in penalizes simultaneously regions with big color

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error and small regions.

This function gives the base idea of evaluation; it's extract some feature in a given pixel correlate to the performance of the segmentation. We modified this function to meet our application. We add a D_j value denotes the color error "Density" if the color difference is distributed in certain small area, which decrease the penalty of wound region, as our hypothesis. It balanced the homogeneity and numbers of region.

$$Q(I) = \frac{1}{1000 \times Na} \sqrt{n} \sum_{j=1}^{n} \left[\frac{e_j^2}{1+\log L(R_j)} + \left(\frac{M(L(R_j)-D_j)}{L(R_j)} \right) \right]$$ Eq 2
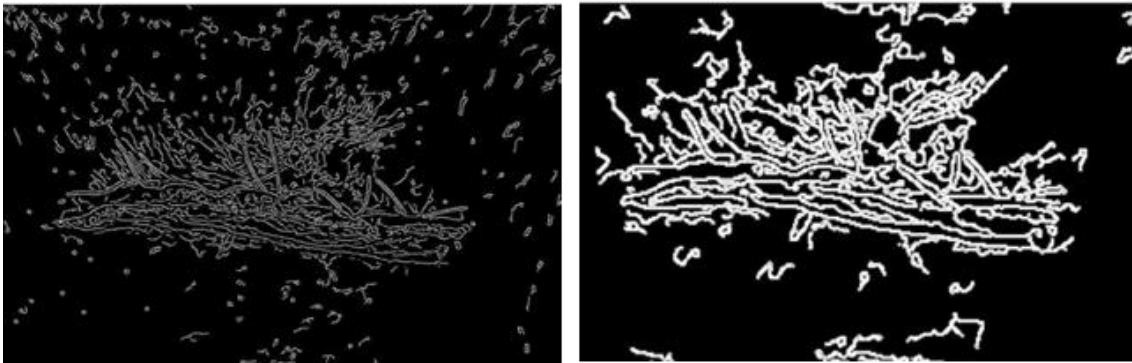
Lower D value   Higher D value

figure 14 Different D value

If the edges are constrained in a more convergence area, D value increases and suppressing the second terms. e_j^2 was define as :

$$e_x^2(R_j) = \sum_{p \in Rj} \left(C_x(p) - C'_x(R_j) \right)^2$$ Eq 3

while

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$$C_x(R_j) = \left(\sum_{p \in Rj} \in C_x(O)\right)/S_j \qquad \text{Eq 4}$$

Secondly, Chen et al[8] proposed a function Ecw.

$$Ecw: \sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} [\mu(TH - ||C_x^0(P) - C_x^s(P)||_{L*a*b}) * w_{i,j}/(S_I * Z)] \quad \text{Eq 5}$$

$w_{i,j}$ denotes the jointed length between Ri and Rj, Th is the threshold to judge difference. $C_x^0(P)$ and $C_x^s(P)$ are pixel feature value for p on original segmented image.

This function uses inter region color difference defined as the pixels whose color difference between its original color and the region average color. Jointed length $w_{i,j}$ means the boundary length between the region and the separate regions.

Since the wound average color may have a huge difference against skin region and noise doesn't guarantee a bigger color difference (if so, it will be detected by *Eq-2*) and tend to have a bigger *busyness,* so we introduce the third function. Zhang et al. [12] proposed an information theoretic approach for segmentation evaluation, E function, based on entropy theory and the minimum description length principle (MDL).

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Given a segmented image, define Vj as the set of all possible values associated

with the luminance in region j. Lj(m) denotes the number of pixels in region j that have

a value of m for luminance in the original image.

The entropy for region j is defined as:

$$H_v(R_j) = -\sum_{m \in V_j} \frac{L_m(R_j)}{L(R_j)} \log \frac{L_m(R_j)}{L(R_j)}$$

Eq 6

Next, they define the expected region entropy of the segmented image,

$H_r(I)$ as:

$$H_r(I) = -\sum_{j=1}^{n} \left(\frac{L(R_j)}{S_j} \right) H_r(R_j)$$

Eq 7

$H_r(I)$ is the expected entropy of each region. It has a similarity to the first term of

Eq-1, which denotes the squared color error. This entropy has to combine with a term

that penalizing the over-segment. Just like the second term in Eq-2, they introduced a

term called layout entropy

$$H_l(I) = -\sum_{j=1}^{n} \frac{L(R_j)}{Na} \log \frac{L(R_j)}{Na}$$

Eq 8

Finally, they define an evaluation function, E, it denotes a lower intra region

entropy, which means a more homogeneous distribution of pixel and a low inter region

value which indicate a inter-region disparity. Lower entropy means a better

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segmentation. Or a more uniformly segmented region. Which is helpful in our

application.

$$E = H_l(I) + H_v(I) \qquad\qquad\qquad \text{Eq 9}$$

Combining these evaluation functions. We can evaluate the region by color

error, region disparity, over-segment and region homogeneity, by these evaluation, we

try to describe the difference between noises, foreground artifact and the wound region.

2.3 Optimization and Genetic algorithm

figure 15 Optimization of the model

Once we describe the problem with a mathematical model, we can solve it with

several techniques. Since this is a multi-objective optimization and we don't have

enough boundary condition for mathematical approach, we used genetic algorithm for a

partly optimal solution by approximation. Genetic algorithm is a "algorithm" comes

from nature genetic behavior, but different from algorithm, it does not guarantee to stop

at certain condition and no decision variables, its encodes problems into chromosomes

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and search from population rather than single point. Most importantly, it uses localized

and randomized operators instead of global, deterministic rules.

First will introduce the encoding procedures and simple GA, take bit flipping as

example, we initial a string of bit as a binary coding, with a fitness function:

$$f(p) = 31p - p^2$$

p can be encoded as a 5 bit string. In each iteration (generation), a possible solution

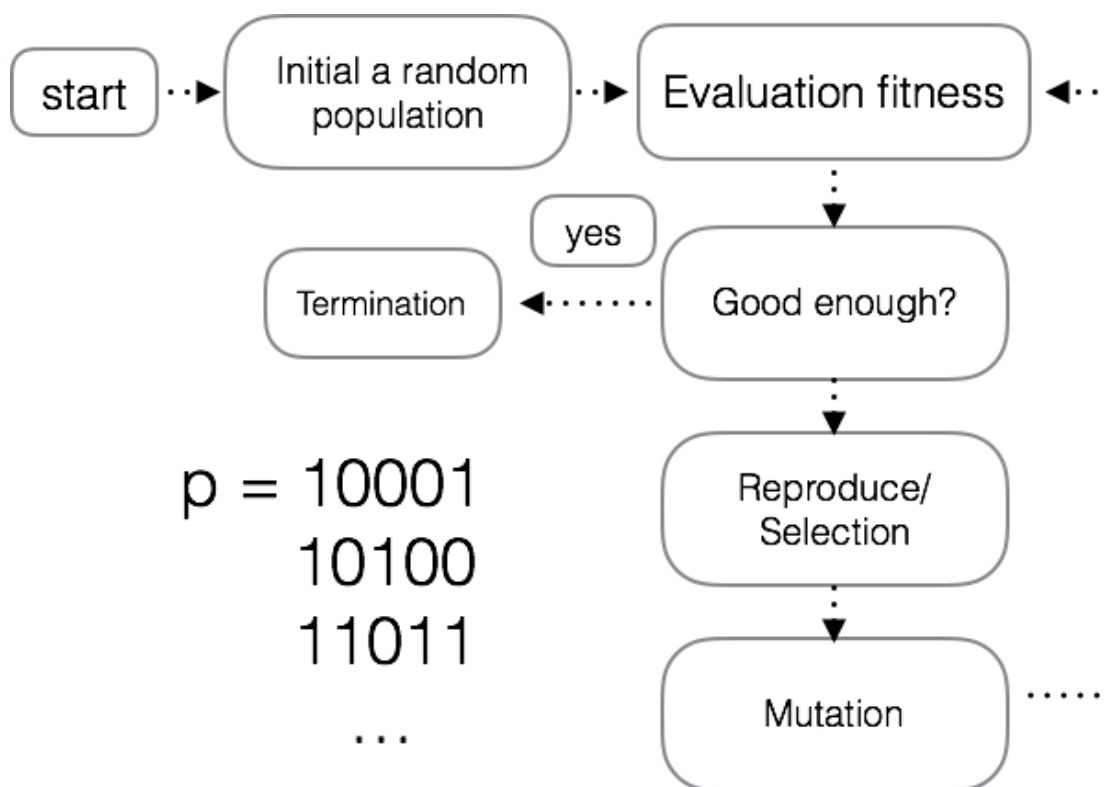(individuals) represented as a string. The whole search space contains 2^5 in this

problem.

figure 16 An example of Simple Genetic Algorithm

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This is an easy optimization problem, which can converge relatively quickly and generate the following result. It is clear that the optimal value is around 15/16.
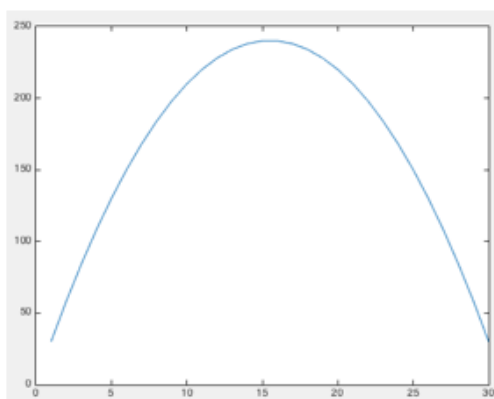
fitness function: 31p-p^2

figure 17 fitness function of the example

The searching procedure is performed by selection, crossover and mutation, which is a 'pseudo-random walk' in the search space.

First operator is selection, under selection pressure S, we produce S selection from the whole generation and make them crossover. There are many selection operators, the basic idea is to select some populations to do crossover, and it may base on rank such as tournament selection. Randomly pick S populations into a tournament, S is the tournament size (equivalent to selection pressure) Select the best guy and put it into the mating pool. Or proportionate selection such as roulette wheel selection, it generate a

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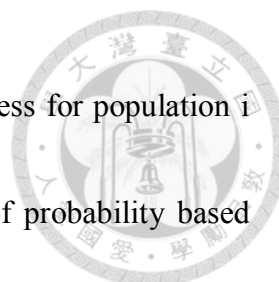
probability associate with the fitness for each population. If the fitness for population i

denotes as fi, the probability of selection $p_i = \frac{f_i}{\sum_{j=1}^{n} fj}$, this kind of probability based

selection tend to convergence faster while it may produce bias. The decision of selection

operator can base on the complexity and the noise of bias.

By selection, we have the candidate of parent population, then perform crossover

operator on them to generate the next population. Crossover also has some different

operators, M-point XO and Uniform Crossover.

M-point XO is randomly or selectively chose M point on parent generation and

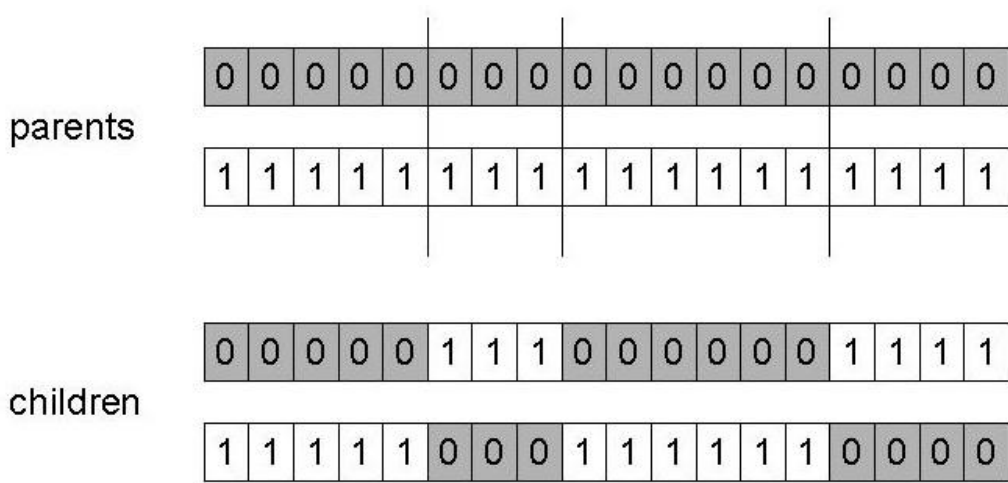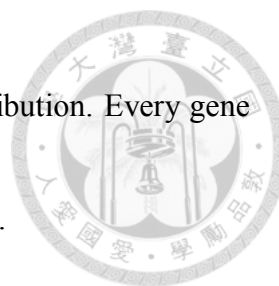performs a crossover inter-string to produce a children generation.

figure 18　M-point crossover

Uniform Crossover is a crossover undergoes a probability distribution. Every gene

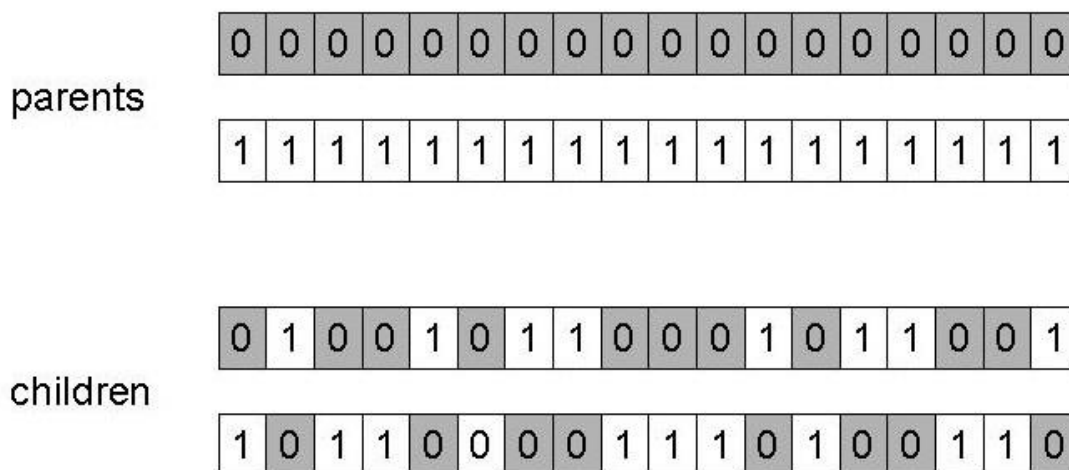comes from dad with probability p, from mom with probability (1-p).

figure 19 Uniform Crossover

Different crossover technique will produce different bias and effect the

convergence of GA, in [19] Eshelman et al discussed the bias of crossover bias,
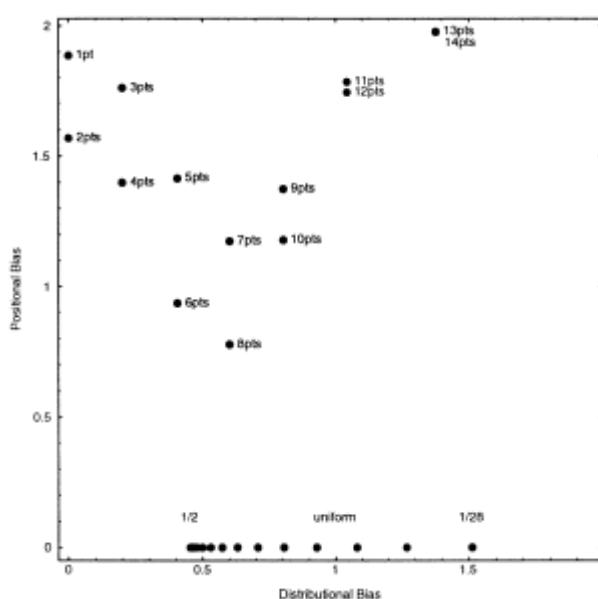
figure 20 Crossover bias

Positional bias described the probability that two genes transfer together depends on their positions, while distributional bias is about the probability distribution of the proportion of genes coming from one parent.

Mutation is a random operator to enhance diversity. Each component of every individual is modified with probability p_m, once the mutation happened, the mutate loci randomly flipped.

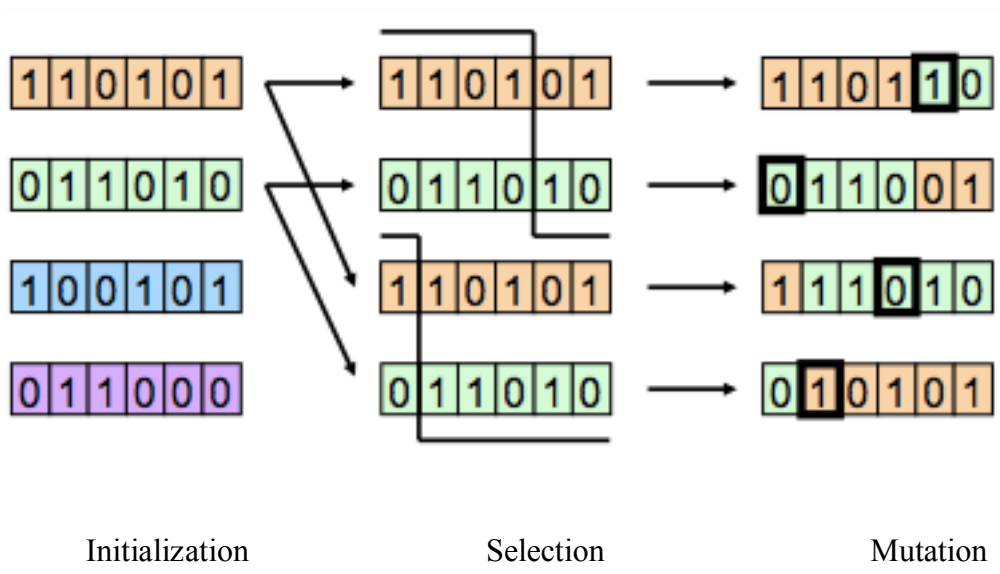Initialization   Selection   Mutation

figure 21 SGA operator

Some GA include replacement and elitism mechanism, Elitism means if the fitness meets certain criteria, the population might produce the generation inherit the performance, it makes sense to keep this elite for faster convergence, while doing so

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might also induce bias and the possibility of premature convergence.

Last part of GA is the termination conditions, since it does not guarantee convergence and only partial optimal, it is a trivial to set the time constraint. Some literature [18] propose that GA should stop when the solution is converge to certain satisfactory, or stop when the population lose its diversity. While the time constraint being chosen, it is a dilemma whether chose a large population and run a fewer generation or small population with longer duration.

For our optimizing problem, it has multiple objectives with non-conflicting object. It can achieve simultaneous optimization while there is still diversity between objects. The more uniform the image is, it is much easier for this algorithm to exclude the right segmentation, since the optimal threshold will be relatively high, more over, the low diversity image, or noise-less image is easy for the wound segmentation pipeline to process. On the other hand, if the input image has higher intra region entropy, lower threshold will more likely to include more information for Eq-7 to evaluate, but it also results in a higher color error.

To solve this kind of optimization problem, Konak et al conclude a tutorial [18], a

general approach to multi-objective optimization is to determine an entire Pareto optimal solution set or a subset which is representable. Moving between the Pareto set is always a certain amount of sacrifice between objectives.

It also makes sense to introduce weighted sum to our objectives, each fitness function was normalized by a scalar.

$$\min z = w1z1(x) + w2z2(x) + \cdots + wkzk(x)$$

Combining all the method we developed a segmentation algorithm and implement an application system.
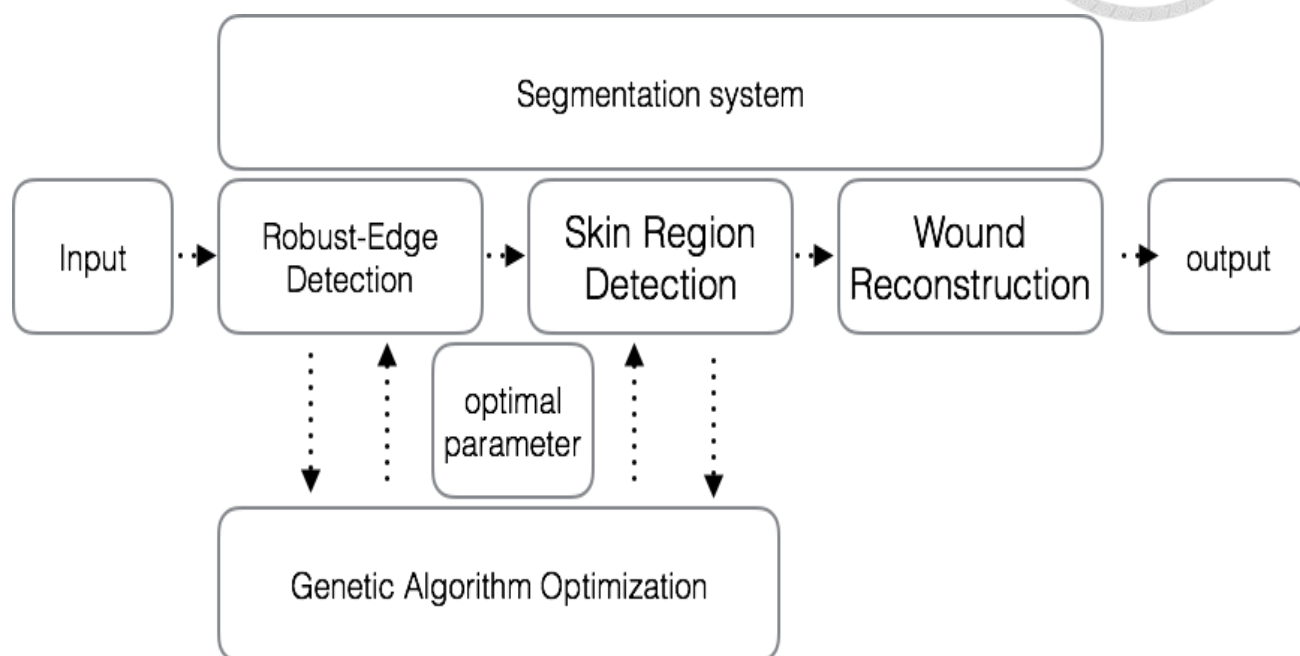
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Chapter 3 System architecture

figure 22 System overview

Each image input will go through the segmentation pipeline; GA optimization is an option since the result is somehow satisfactory, using GA for optimization provides a boost of accuracy while needs additional computing times. GA is used to optimized the threshold of edge decision and the threshold of differentiate the noise and skin region.
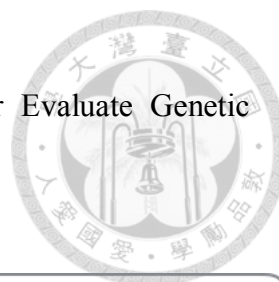
Look deeper inside the GA system, we adapted the Vector Evaluate Genetic
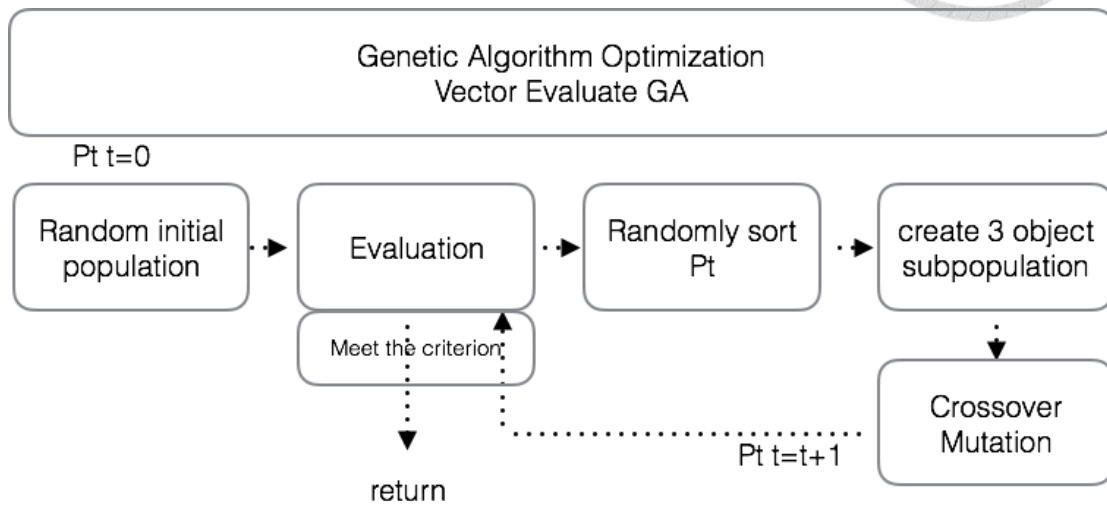
algorithm proposed in [[18].

figure 23 VEGA

Subpopulation was creating by following step. For each objective k, k=1, … ,K,(In

our problem, K=3), For i = 1 +(K-1)N_s,…,KN_s, assign a fitness value $f(x_i) = z_k(x_i)$ to the

ith solution in the sorted population Pt. Based on the fitness value assigned, select N_s

solutions between the $(1+(K-1)N_s)$th and (kN_s)th solutions of the sorted population to

create subpopulation P_k. Combining P1 to Pk and apply Crossover and mutation

operator to create P_{t+1}. Here we use one point XO and Uniform XO.

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Chapter 4 Result

4.1 Experiment environment

The following experiment was run on intel i7-6700 with 16gb ram and NVIDIA

GTX 970 GPU. With total 127 sample images. 107 with wound and 20 with normal

skin.

4.2 Execution time

Performing the segmentation algorithm on the data set of 127 image, the average

execution time is 23.15 sec, the bottleneck of segmentation algorithm is the robust edge
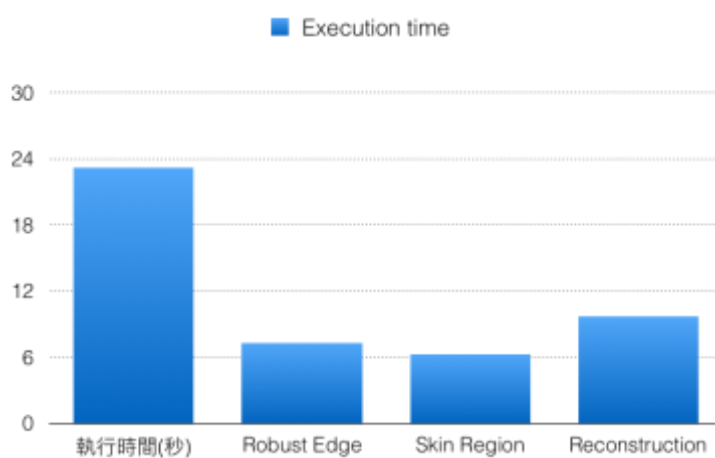
detection and wound reconstruction.

figure 24 Execution time
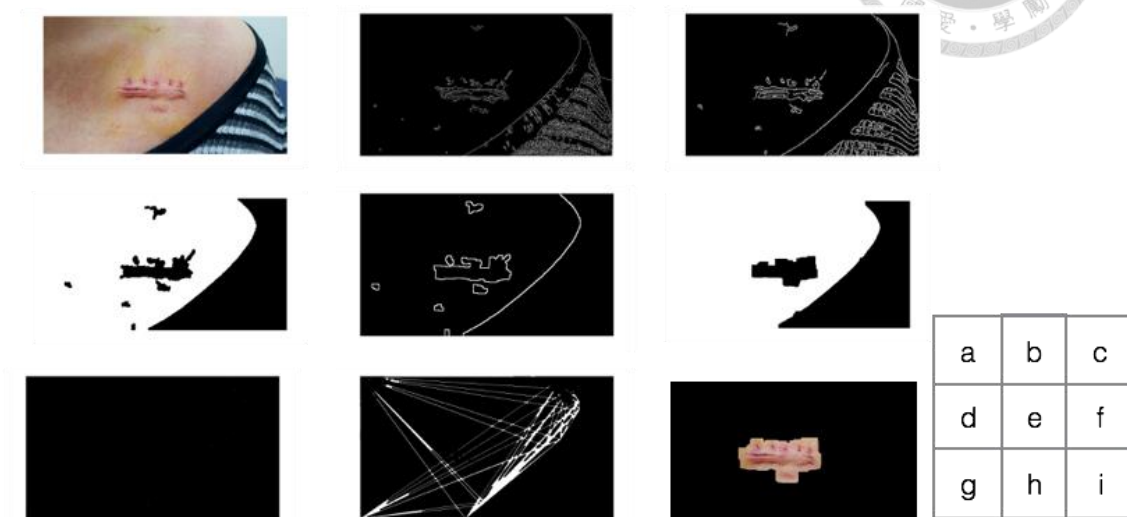
4.3 Segmentation Result

figure 25 Example of the segmentation algorithm

This is an example of the segmentation algorithm, (a) The input image, (b) The first result of canny edge detector, (c) Result of robust edge detection. (d) Performing morphological operator on the robust edge and compare with skin color model. (e) Detection of different region for the wrinkle count. (f) After the wrinkle count, the algorithm gives a prediction of wound mask. (g) Wound reconstruction starts, this picture is the result of Skeleton and Endpoint operator. (h) Connect the endpoint to construct the true skin region. (i) Final result, overlap the reconstructed wound region and the mask given by (f)

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By performing this segmentation algorithm, it segments out the whole wound

region in 81 picture out of 107.

While some of them are exception cases, the robust edge gives the result of the
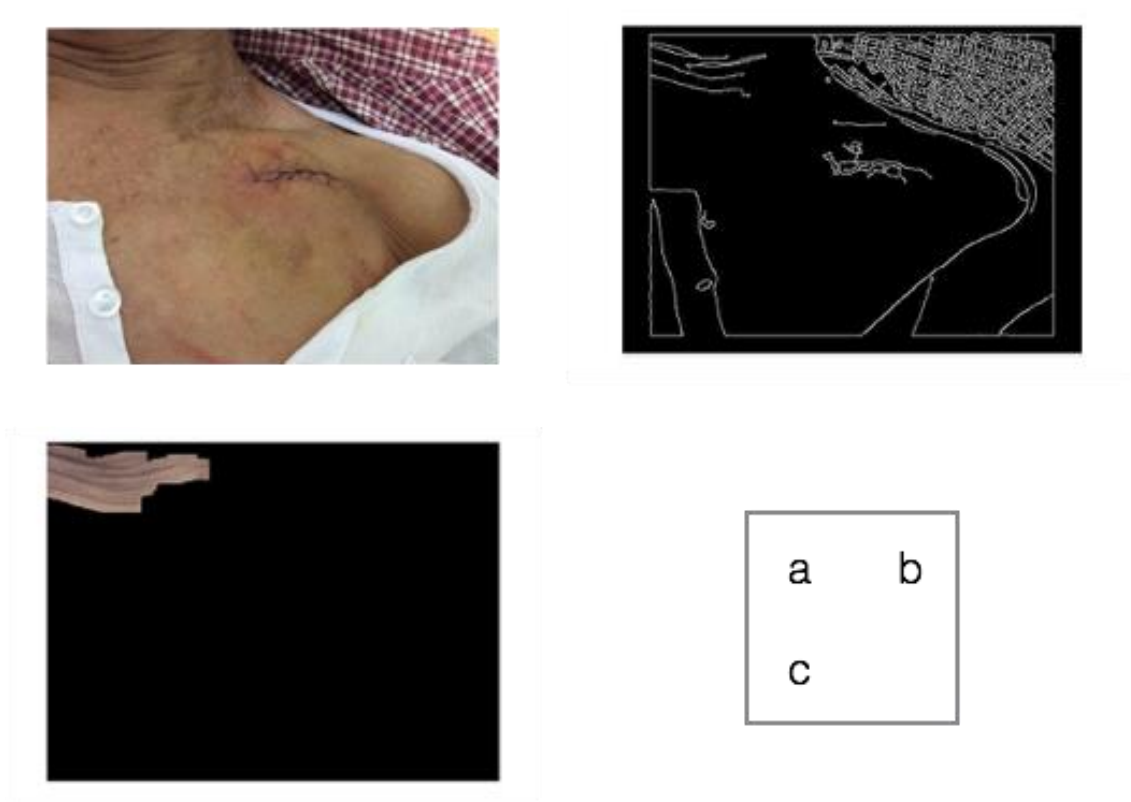
background noise or artifact.

figure 26 example of exception

The wrinkle on the patient's neck exceed the robustness of the wound. Despite

the robust edge did find out the wound region in picture (b) and eliminate the noise f

background clothes by skin region. So we adapt the optimization part.
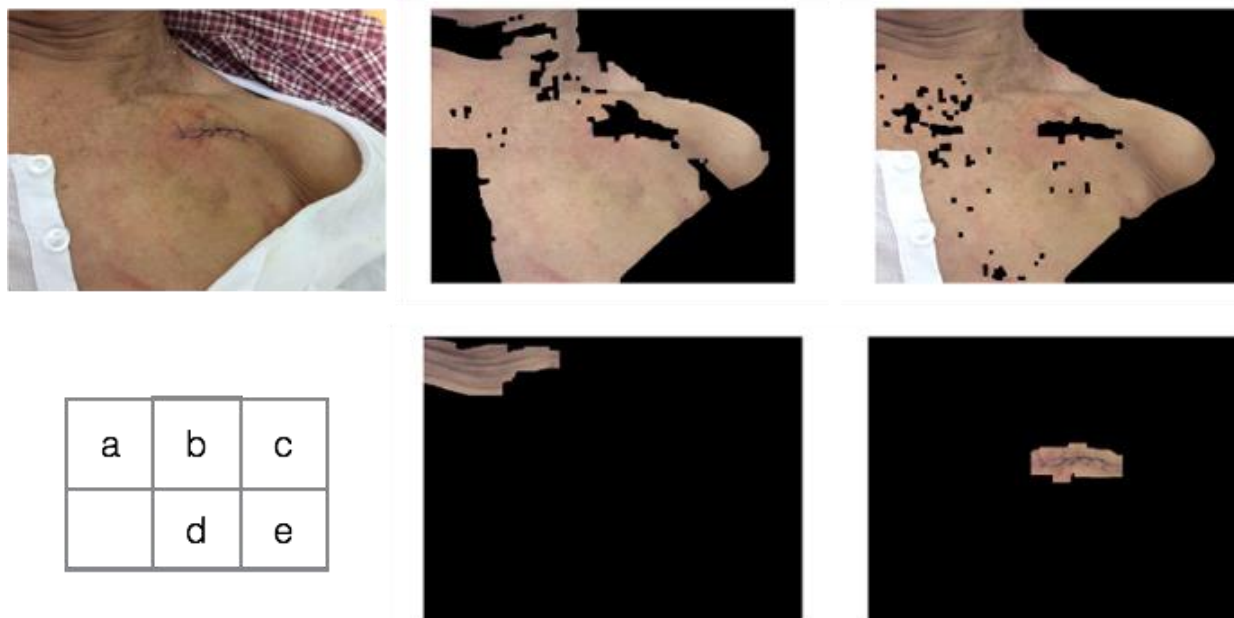
4.4 Result of GA Optimization

figure 27 Optimization result

Picture a is the original input. Picture b and c are the different generation of GA output, since b is a local optimal so it is possible to convergence in b, but by our evaluation function, we obtain the correct result of the wound in picture e. The threshold is automatically chosen by the evaluation function, the distribution of fitness function does not always a simple distribution like the example we see in figure 17. So the termination was set when the population loose it's diversity. Following are more example about how threshold was autonomously chosen by GA optimization
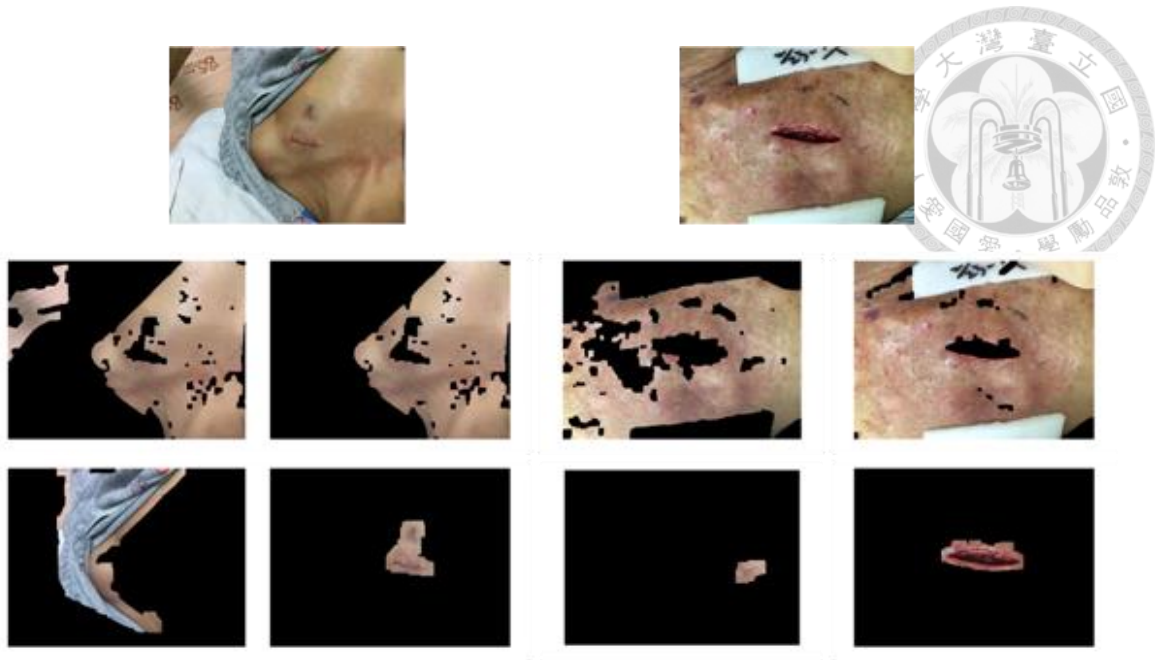
figure 28 Different threshold of skin region

Chapter 5 Conclusion

In this literature we proposed an image segmentation method for wound region

segmentation and extraction. Which is of a great use for the following analysis, the

evaluation function does work on our data set while achieving a relatively high accuracy.

The unsupervised evaluation function is mostly empirical and application-dependent,

the function we modified is suitable for our application scenario but also gives a

dilemma between large region and color error. This optimization needs much more

computing power than the original segmentation algorithm which is also a trade off

between speed and efficiency.

Chapter 6 Future work

We'll try to propose a more suitable evaluation function to avoid the dilemma of region problem and give an optimization without using evolutionary algorithm due to the application scenario of mobile computing, if we can prove the search space to be a convex, it might be able to use a gradient descent algorithm to achieve the global optimal. We'll further implement an integrated system connecting segmentation and analysis procedure

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