Medical Image Analysis

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Introduction

- Image Significance
  - Chinese say 1 Image is 1000 words
- Image Processing is a well established scientific field
  - has 2 goals
    - Image enhancement for human observer
    - Image analysis for computer vision
- Extraction of features representing meaningful information from images

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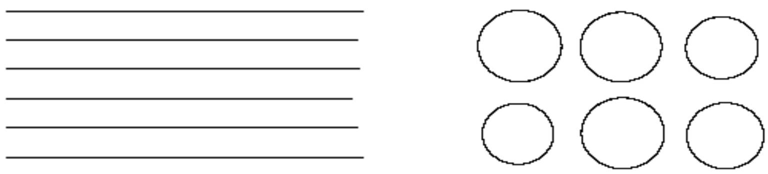
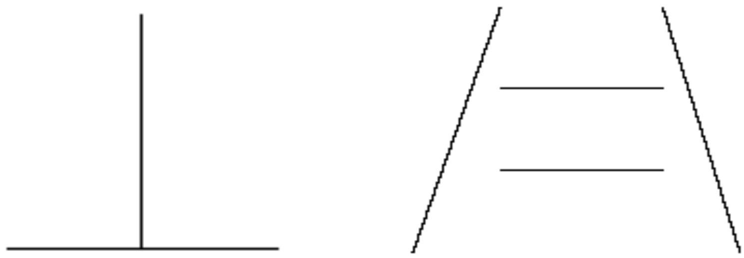
Human vs Computer Vision



Human vs Computer Vision

- The differences in the legth of parallel lines are noticeable
- But what happens with the areas of the circles

Human vs Computer Vision

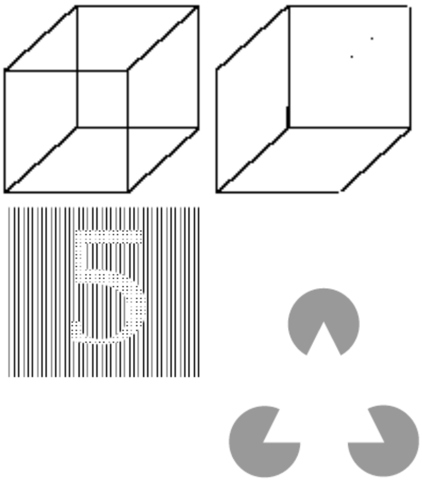


Human vs Computer Vision

- The lines have the same length
- But their orientation gives another impression

- The same stand for the side lines…

Human vs Computer Vision



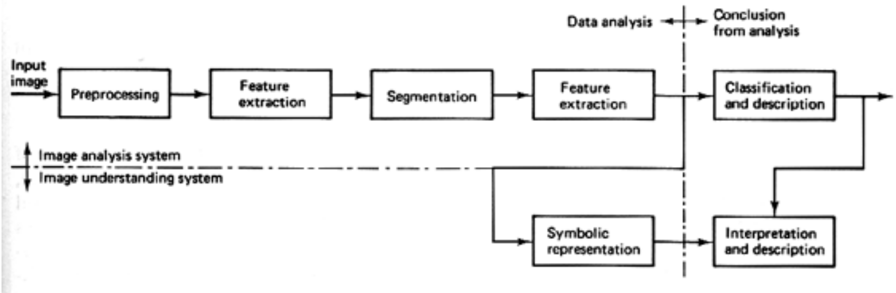
- Visual occlusions
- Human observer
  - Can estimate the 3rd dimension of the illustrated object
  - Can understand the content (figure)
  - Project the sides of the hypothtical triangle

Which is better…

- Human Vision
  - Rapid Processing
  - Complex Knowledge Based Sensing
  - Content Interpretation
- Computer Vision
  - Accurate Processing
  - Reproducible Results
  - Batch and non-stop processing
  - Sees in non visual spectrum

Image Analysis in Biomedicine

- Significant increase in the level of interest in biomedical image morphology, full-color image processing, image data compression, image recognition, and knowledge based biomedical image analysis systems.
- The goal is the development of tools, which are designed to serve as diagnostic adjuncts for medical professionals and assist biologists in measuring biological mechanisms



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Issues to be addressed in Medical Image Analysis

- How can we acquire good images or correct already captured ?
- How can we segment medical images? i.e. separate ROIs in images (image segmentation)
- How can we register medical images for follow ups?
- How are the image features defined, i.e., what are we looking for?
- How are these features detected in the image? (trivial for humans but non-trivial for machines).
- Which are the proper features to use and how many are they? (feature selection).
- How do we use the features to design the classifier for the specific task,
- How can we assess the performance of a classifier?

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Image Acquisition is the first step

- Quite Important for the next steps
- Need for standardization
- Sensor Calibration
- Variety of Sensors

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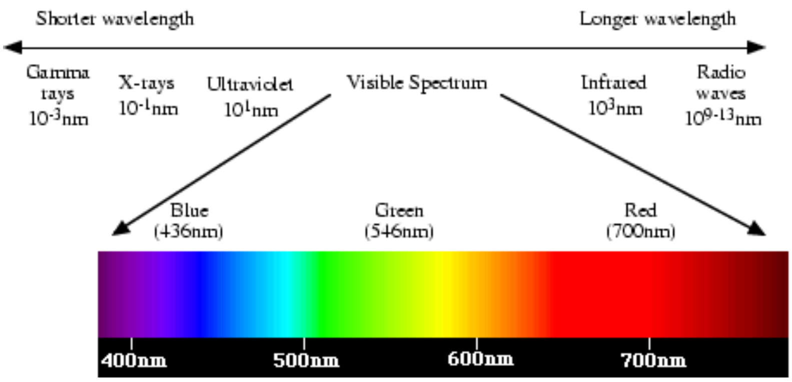
The visual spectrum



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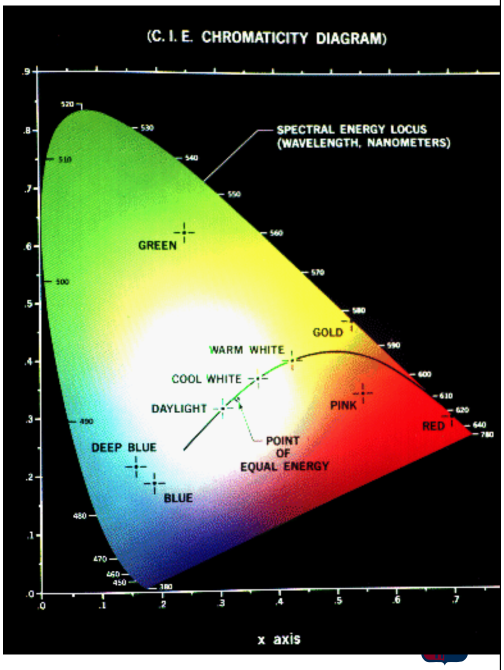
Basic Colors

- All colors are a combination of **R**ed, **G**reen and **B**lue
- Determined by CIE (Commission Internationale de l’ Eclairage - the International Commission on Illumination)
- Normalized Values
  - r= R/(R+G+B) = x
  - b= B/(R+G+B) = y
  - g=1-r-b



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UV skin image

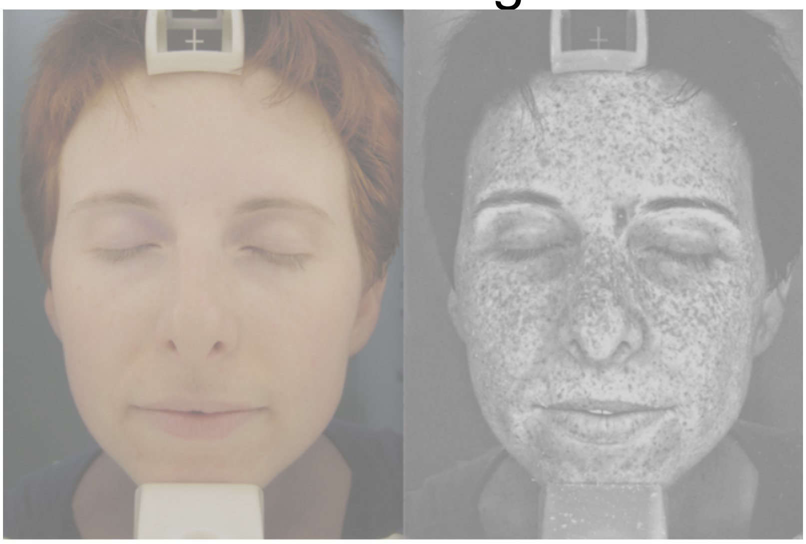

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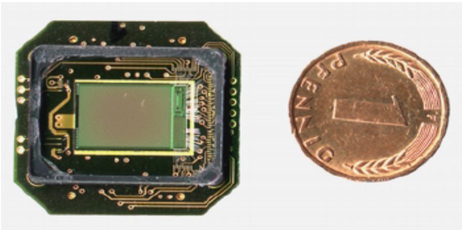
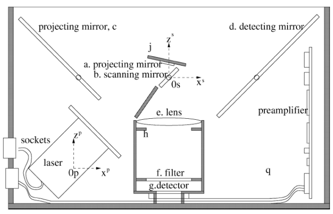
Image sensors



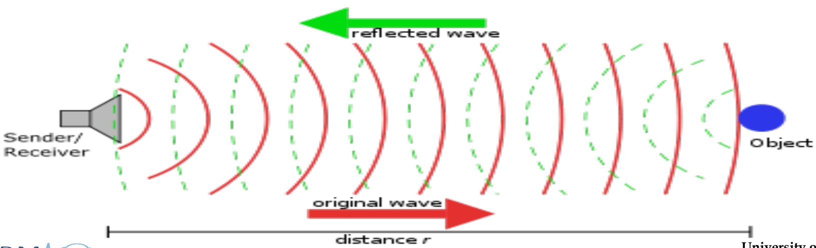
- Left: CMOS camera
- Right: CCD camera high fidelity

Other Sensors

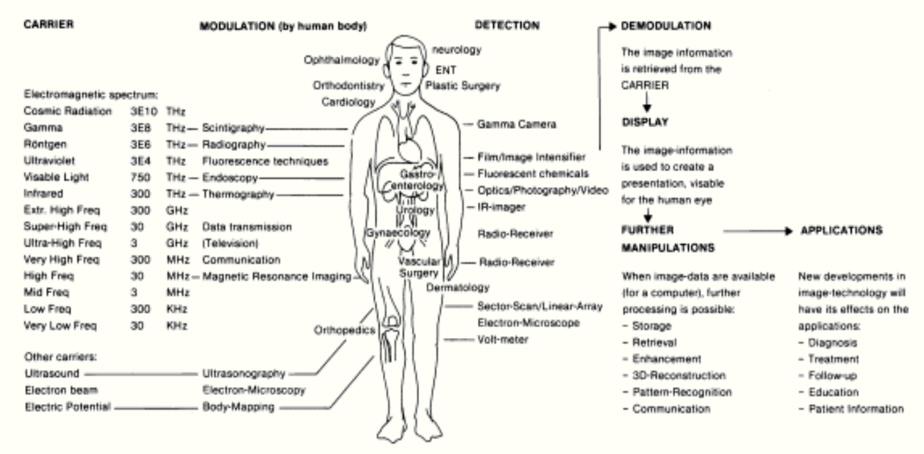
- Laser Sensors



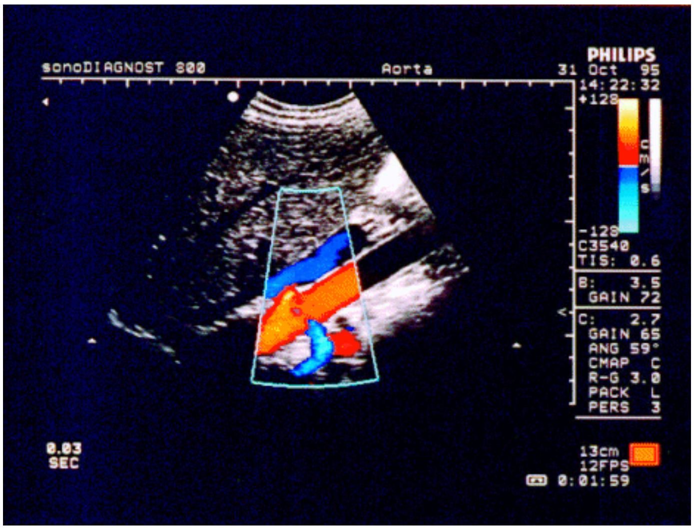
- Ultrasound sensors



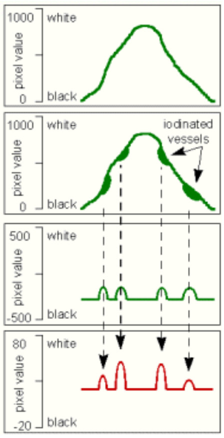
Medical Images



Sector scan Ultra Sound



Digital Angiography (DA)



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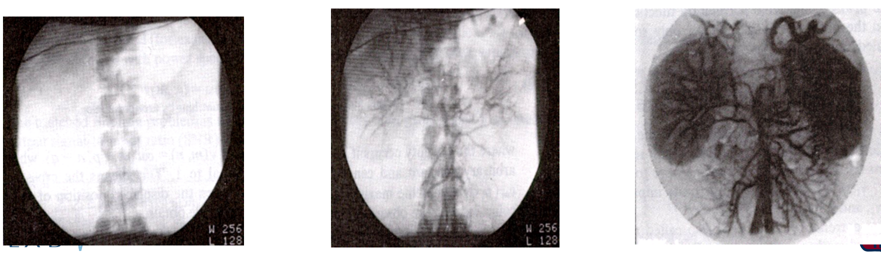
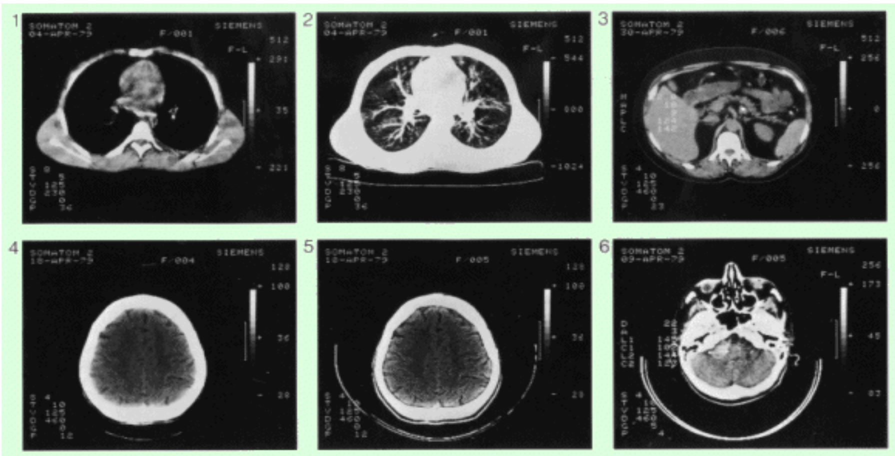
Digital subtraction angiography (DSA)

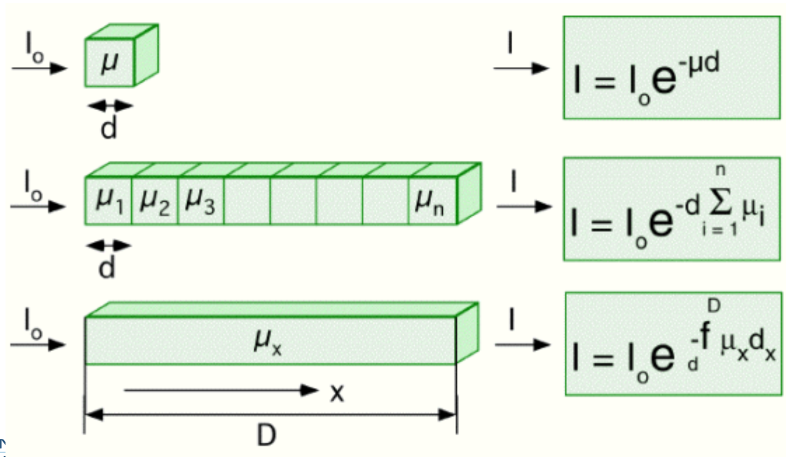
DSA example of a kidney image : (a) original image, (b) after contrast agent provision (c) subtraction (a)-(c).



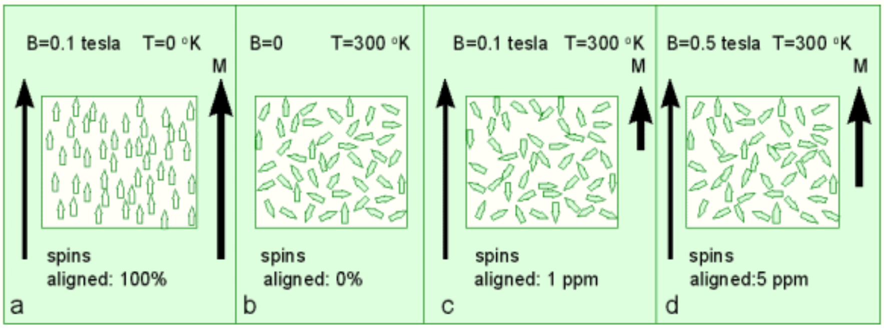
Computed Tomography



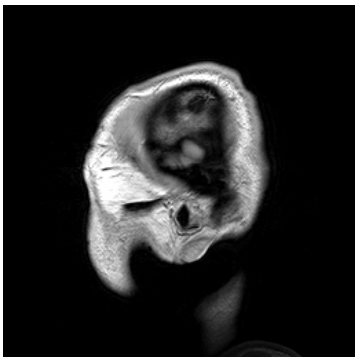
Computed Tomography



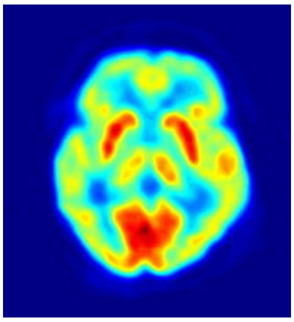
Magnetic resonance imaging (MRI)



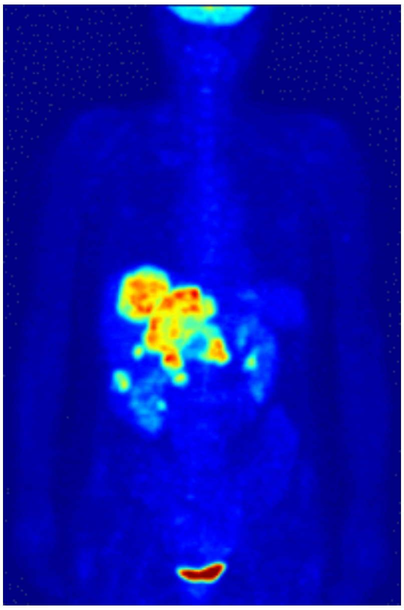
MRI



- http://www.patiencys.com/MRI/



BRAIN PET



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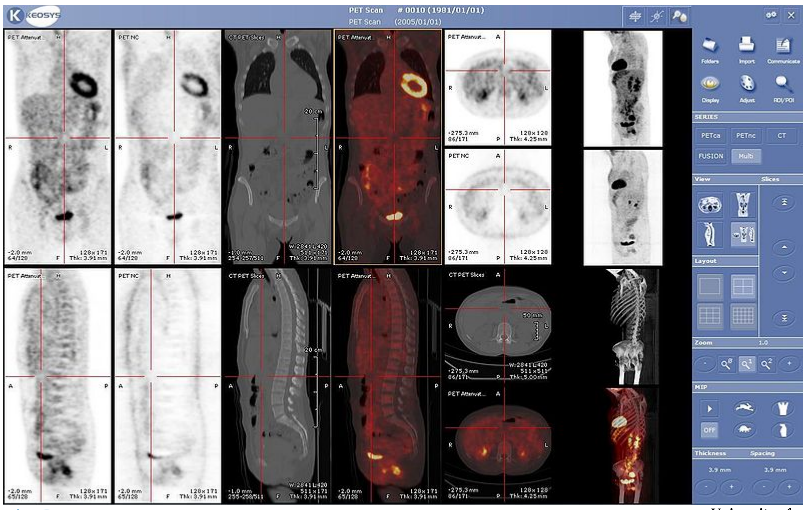
PET – CT



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PET - MRI

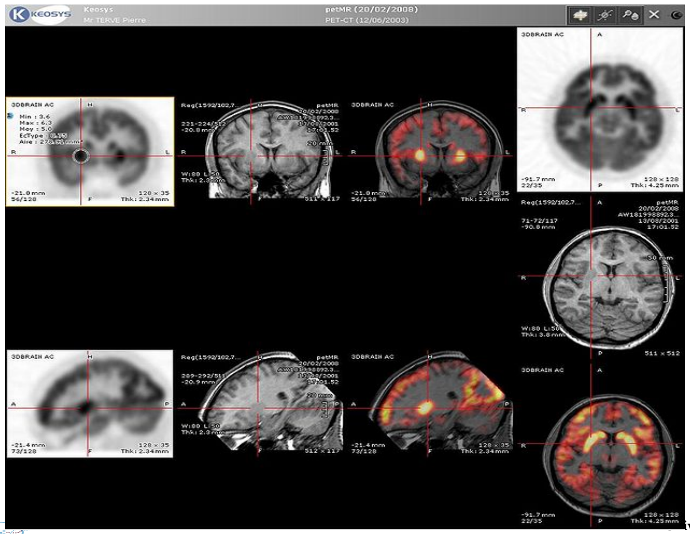

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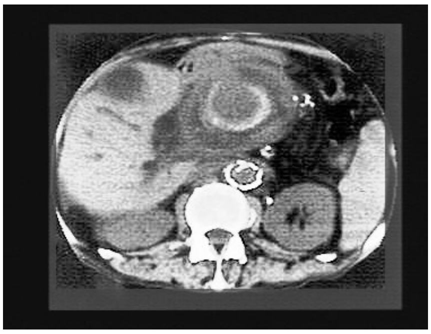
Image Preprocessing: the first step

- Image Enhancement
  - Contrast Enhancement
  - Histogram Equalization
- Image Restoration
  - Filtering
    - Space Domain
    - Time Domain

Example HistoEqualization



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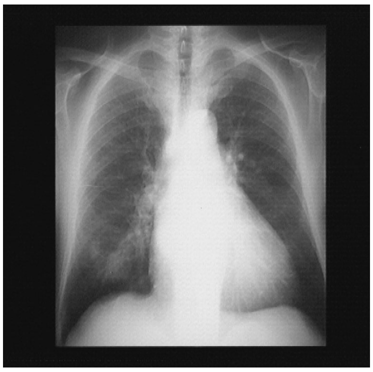
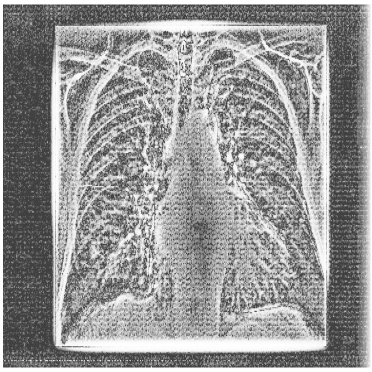
High Pass Filtering





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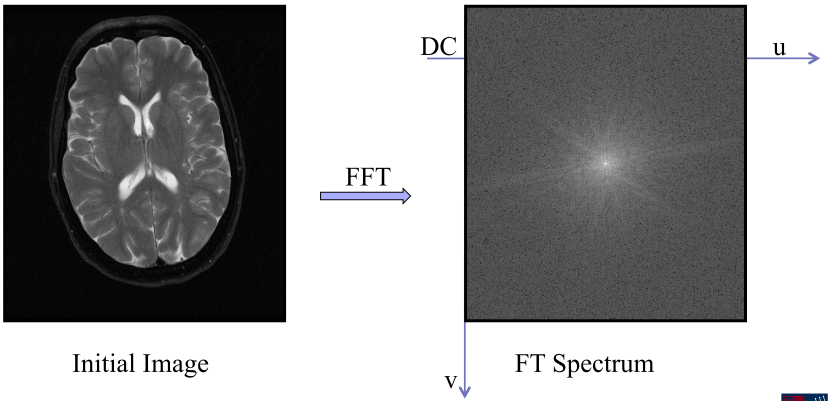
Example of FT in MRI



Initial Image

FT Spectrum

Image Segmentation

- *Segmentation* is the process of partitioning a digital image into multiple segments (sets of pixels) corresponding to objects. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.

Basic Approaches

- Thresholding Adaptive or Global
  - select a threshold value (or values when multiple-levels are selected)
- Edge detection
- Region-growing methods
- Split-and-merge methods
- Active Contours or Snakes

Adaptive Thresholding

α

β

Edge Detection – Convolution with Prewitt Operator

109	112	113	108	106	115	108	105
106	111	116	110	111	107	112	113
118	113	112	110	113	115	112	109
110	111	114	117	110	115	107	110
190	191	179	180	191	185	183	181
178	180	185	187	190	188	185	183
190	191	179	182	191	190	187	186
183	179	184	189	194	189	188	183

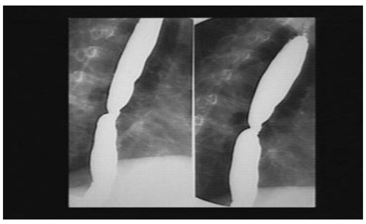
$\otimes$

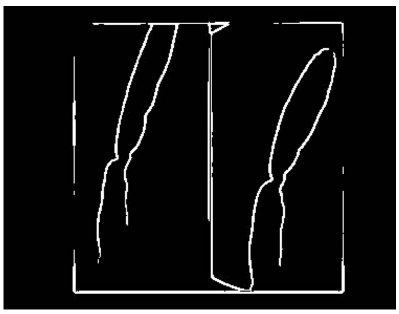
-1	-1	-1
0	0	0
1	1	1

$=$

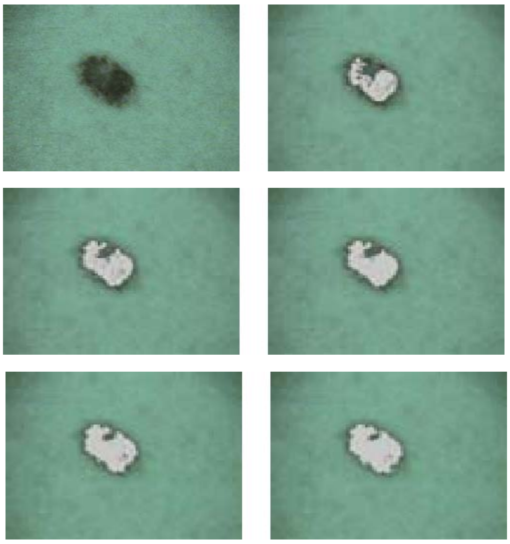
9	2	8	9	11	8
2	5	4	14	2	0
217	215	215	218	219	213
208	210	221	223	231	224
0	2	2	7	9	14
3	0	5	7	8	4

Edge Detection



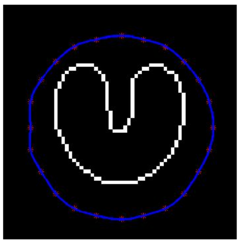


Region Growing

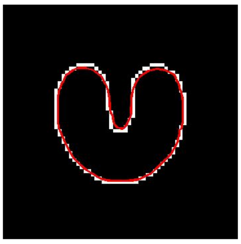


Active Contours and Active Surfaces

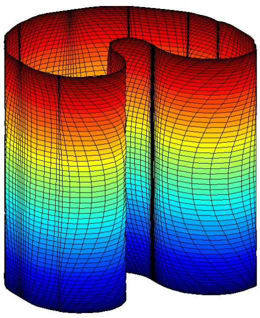
- Image segmentation method
- Snakes or active contours (AC) are curves that deform, according to the local influences of the image
- Active surfaces (AS) are the 3D version



Snake initialization



Converged snake



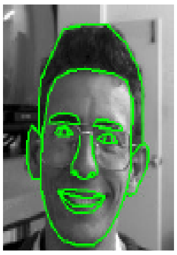
Converged active surface

Active Contours

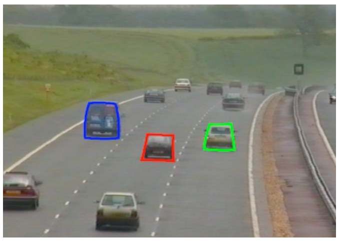
- Active Contour (Snakes) are considered as energy-minimizing splines, guided by external constraints, internal and image forces.
  - Snake : Energy function to be minimized.

$$E_{snake} = \int_0^1 E_{\text{int}}(v(u)) + E_{image}(v(u)) + E_{ext}(v(u)du$$

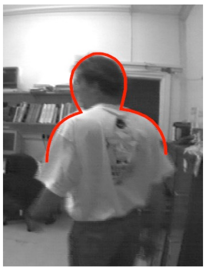
Active Contours



Face Recognition

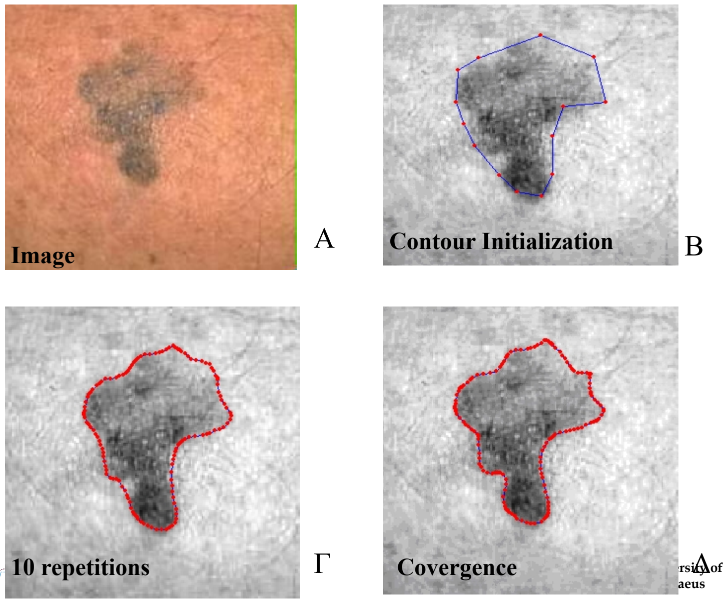


Traffic Monitoring



Surveillance

Active Contours



The final steps…

- Feature Extraction
  - Involves using algorithms to detect and calculate quantified characteristics of the whole image (features).
  - Information Reduction
  - Information Labeling – Description of content in the feature space not in the image pixels space

Pattern Recognition or Classification

- Measure similarity in the feature space
- Features should be selected so as to separate and uniquely describe the objects
- Feature types:
  - Spatial features , geometrical and border features
  - Texture or Color features
  - Transformation features

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Case Study Application in Dermatology: Skin Cancer Recognition

- Diagnosis of skin lesions is based on visual assessment of pathological skin and the evaluation of macroscopic features.
- High dependency of the correct diagnosis on:
  - The observer's experience and on his or her visual acuity
  - Observation Geometry
  - Enviromental Conditions
- Malignant melanoma is among the most frequent types of skin cancer and one of the most malignant tumors
- The differentiation of early melanoma from other pigmented skin lesions is not trivial even for experienced dermatologists

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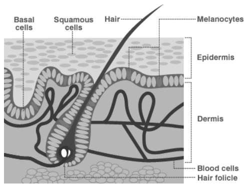
The image mechanisms of skin cancer



Normal skin lesions and main components (source: MediceNet)

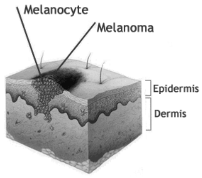


Illustration of Melanocytes and Melanoma on skin (source: MediceNet)

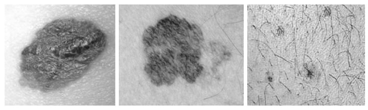


Illustration of (a) typical melanoma, (b) dysplastic nevus and (c) non-dysplastic (common) nevus.

The presence of melanin in the dermis is the most significant sign of melanoma. However, it cannot be used as a sole criterion because in situ melanomas do not have dermal melanin. The colors associated with skin which has melanin deposits in the dermis normally show characteristic hues not found in any other skin conditions. This provides an important diagnostic cue for a clinician.

Skin Image Classification and Melanoma Recognition

Sensor CCD or CMOS → Acquisition, Sampling, Quantization → Preprocessing → Segmentation →

→ Registration (matching) → Analysis Feature Extraction → Image Classification AI Tools → Recognition

I. Maglogiannis, S. Pavlopoulos, D. Koutsouris : "An Integrated Computer Supported Acquisition, Handling and Characterization System for Pigmented Skin Lesions in Dermatological Images" IEEE Transactions on Information Technology in Biomedicine, Vol. 9, Issue 1, pp 86-98, March 2005

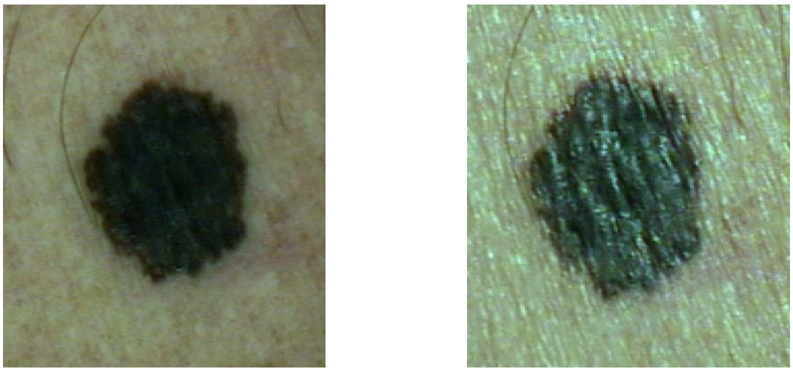
Image Acquisition

- Main techniques used for this purpose are
  - The epiluminence microscopy (ELM or dermoscopy) and
  - The image acquisition using still or video cameras.
  - Multispectral images
- Problem
  - Lack of reproducibility and accuracy due to dependency on equipment and environmental constraints, such as image resolution, image noise, illumination, skin reflectivity and pose uncertainty
- Requirement
  - Image acquisition Standardization and Camera Calibration

Acquisition Corrections

- **Polarizing filters** to eliminate reflections
- **Calibration to black, white and color** performed by comparing camera response to black, white and color standards (Macbeth Color Checker) with their known lightness values
- **Shading correction** performed by division of an image with all pixels having R=G=B=255 by the image of a perfect diffuser and then multiply a captured image with the look-up table generated by the division.
- **Morphological Filtering** for noise reduction, hair and scales removal and elimination of remaining light reflections.

The effect of polarizing filters



I. Maglogiannis : "Design and Implementation of a Calibrated Store and Forward Imaging System for Teledermatology" Journal of Medical Systems, Vol. 28, (5), pp. 455-467 Springer Science Academic Publishers, 2004

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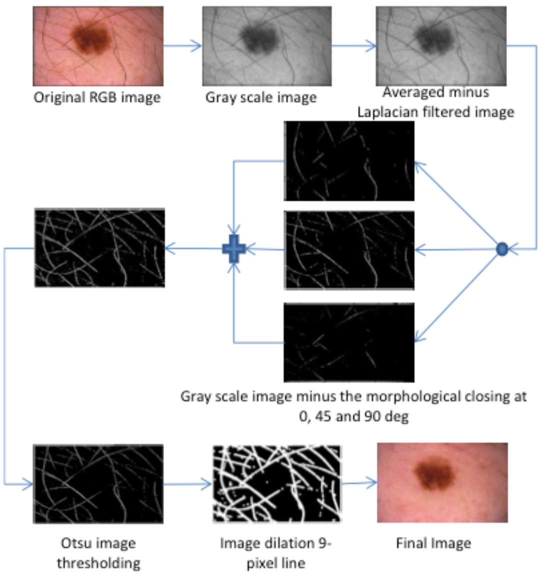
Hair Removal



I. Maglogiannis, K. Delibasis, "Hair removal on dermoscopy images", 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) 2015 pp 2960-2963

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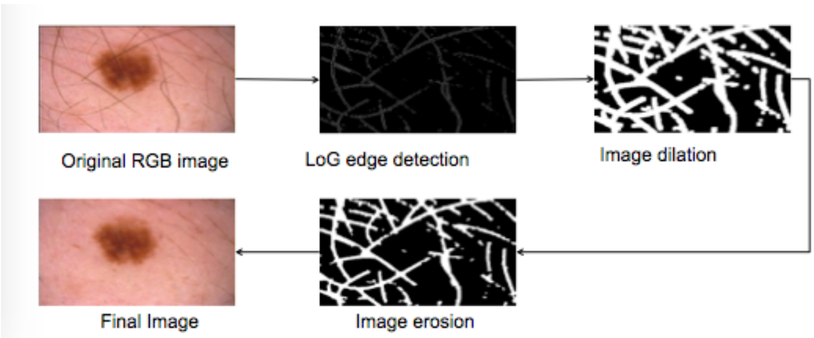
Hair Removal II



Results

Method	SENS	SPE	Q	ACC	MCC	RMSE
Bothat	68.11	93.87	80.99	93.77	0.16	1.47
Laplacian	100.00	84.61	92.30	84.67	0.15	2.48
Logsobel	100.00	79.74	89.87	79.82	0.12	3.06
Log	91.34	94.04	92.72	94.03	0.22	1.72
Lls	100.00	92.32	96.16	92.35	0.21	1.54
Dullrazor	30.73	100.00	65.36	99.73	0.55	6.81

Error metrics

- Accuracy (% of hair pixels removed)
- Specificity (% of non-hair pixels remaining)
- Balanced Accuracy (Sensitivity + Specificity)/2)
- The Matthews correlation coefficient (MCC) and the
- Root Mean Square Error (RMSE) between the original ground truth image without hair and the processed image

Skin Lesion Features I

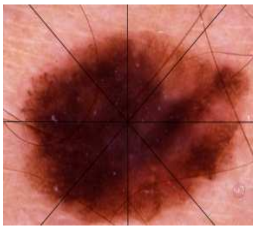
- The ABCD rule of dermoscopy
  - Asymmetry: The lesion is bisected by two axes that are positioned to produce the lowest asymmetry possible, in terms of border, color, and other dermoscopic structures.
  - Border: The lesion is examined if there is a sharp, abrupt cut-off of pigment pattern at the periphery of the lesion piece or a gradual, indistinct cut-off.
  - Color: The number of colors present and their variation is determined.
  - Differential structures: The number of structural components present is determined, i.e., Pigment Network, Dots (scored if three or more are present), Globules (scored if two or more are present), Structureless Areas (counted if larger than 10% of lesion), Streaks (scored if three or more are present).

Skin Lesion Features II

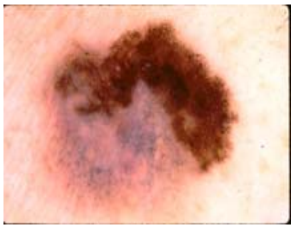
- The Menzies method
  - The Menzies method looks for negative features (Symmetry of pattern, Presence of a single color) and positive (Blue-white veil, Multiple brown dots, Pseudopods, Radial streaming, Scar-like depigmentation, Peripheral black dots/globules, Multiple (5-6) colors, Multiple blue/gray dots, Broadened network).
- The 7-point checklist refers to seven criteria:
  - Atypical pigment network
  - Blue-whitish veil
  - Atypical vascular pattern,
  - Irregular streaks,
  - Irregular dots/globules,
  - Irregular blotches and
  - Regression structures

Asymmetry Border Color

Asymmetry test

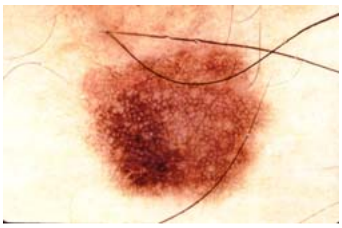


Border test

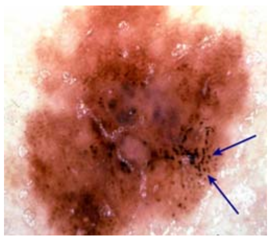


Color counting

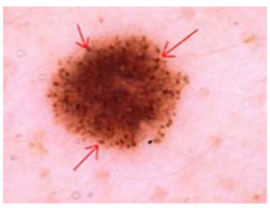
Differential Structures



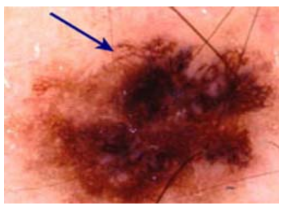
Pigmented network



Dots

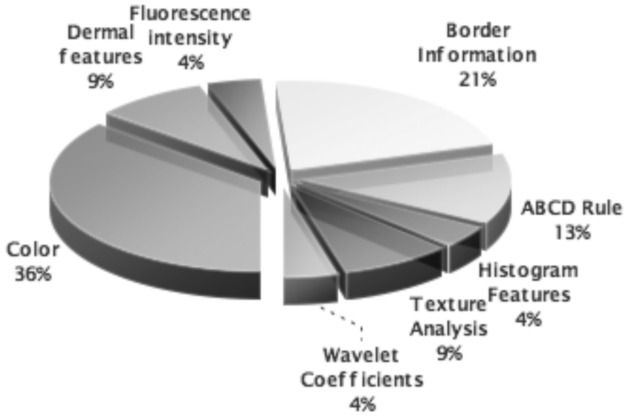


Brown globules



Branched streaks

Illustration of the feature distribution as used by existing systems in literature



I. Maglogiannis, C. Doukas, "Overview of Advanced Computer Vision Systems for Skin Lesions Characterization", IEEE Transactions on Information Technology in Biomedicine Sep;13(5):721-33 2009

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Asymmetry Features

- Examines symmetry with respect to all mentioned features
- Computed by overlapping the two halves of the tumor along the principal axes of inertia and dividing the non-overlapping area differences of the two halves by the total area of the tumor
- Generic region-wise feature: $R_i = \frac{Q_i}{\sum Q_i}$
  - Q_i: individual feature of lesion slice, defined by symmetry axes

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Border Features

Examples of border features used:

- Irregularity $$Irregularity = \frac{Perimeter}{Area}$$
- Thinness ratio $$ThinnessRatio = 4\pi \frac{Area}{(Perimeter)^2}$$
- Variance of the distance of the border lesion points from the centroid

Other feature class: transition from lesion to the skin: minimum, maximum, average and variance responses of the gradient operator, applied on the intensity image along the lesion border

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Color and Texture Features

- Color spaces: RGB, YUV, HSI etc
- Minimum, maximum, average and standard deviations of the selected channel values, chromatic differences inside the lesion
- Colors that are typical for skin lesions may be detected after a color quantization and the percentage of each color in the lesion can be exploited as a feature.
- Color entropy $$C_v = -\sum_{c1}\sum_{c2}\sum_{c3} p_{c1c2c3} \log(p_{c1c2c3})$$
- Color homogeneity $$C_h = \sqrt{\frac{1}{n}\sum_i (\mu_{c_v} - c_v^i)^2}$$

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Differential Structure Features

- Very rare in literature despite their significance in conventional diagnosis
- Potential use of pigment network feature
  - Pigmentary structures extracted in the X-plane of the CIE-xyz space.
  - Calculate a skeleton of the pigment network, and the orientation of the peripheral elements of this skeleton is tested to detect radial streaming and pseudopods.
  - Skeleton is also used for assessment of network hole sizes.
  - Globules extracted in similar fashion

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Feature extraction using image processing

- Image segmentation: involves the separation of the skin lesion from the healthy skin.
- Based on one of two basic properties: discontinuity and similarity.
  - Detection of discontinuities between the skin lesion and the surrounding healthy skin.
  - Pixels, which belong in skin lesion, have different color attributes from pixel corresponding to healthy skin
    - Thresholding is implemented by choosing an upper and a lower value and then isolating the pixels which have values in this range.
    - Region Growing is a procedure that groups pixels or subregions into larger regions.
    - Clustering initially divides the image into rectangular regions small enough to be considered as having only a single color. This is followed by conservative merging, where adjacent regions whose colors are similar are connected.

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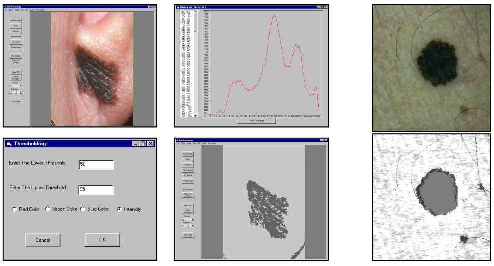
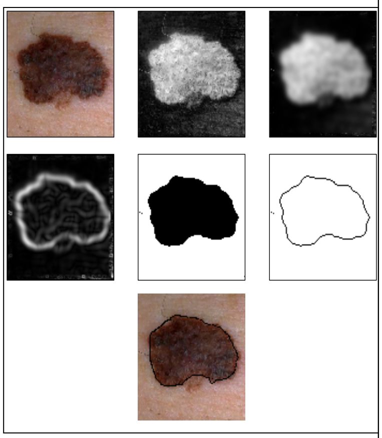
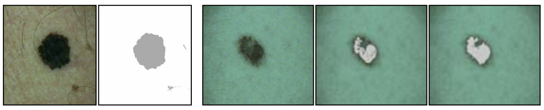
Examples



A) Thresholding D) PCT Transform



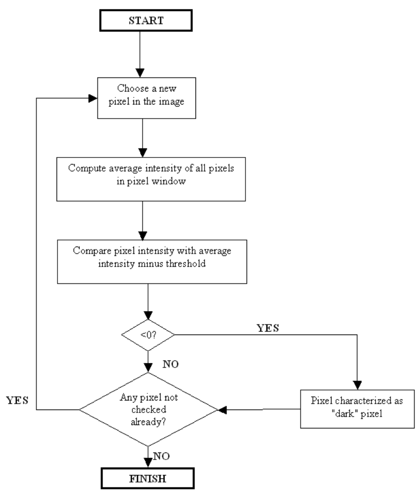


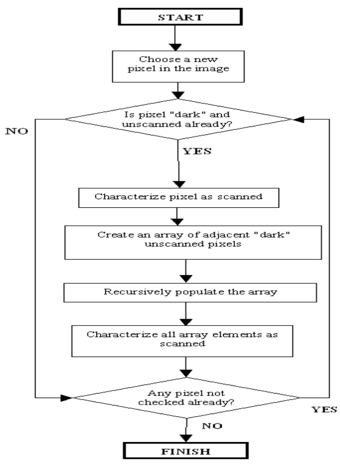
B) Use of weighted functions

C) Region Growing

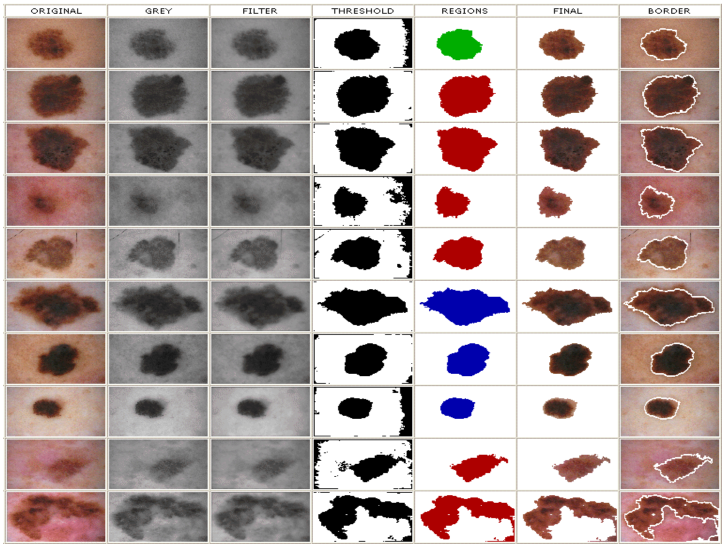
E) Edge Mapping

Adaptive thresholding and lesion extraction algorithms' flowcharts





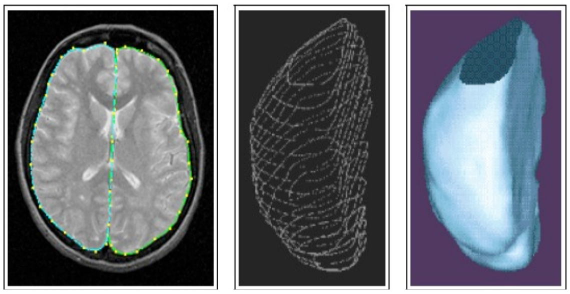
Adaptive Thresholding Segmentation (a) original image (b) grey scale image (c) smoothed image (d) adaptive thresholding (e) object extraction (f) segmented image



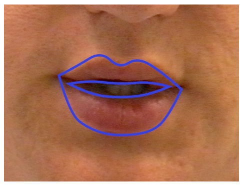
The Active contour or Snake approach

- Active contour models have gained lately large acceptance as a segmentation tool since they support interactive mechanisms in order to guide the segmentation.
- The main idea of active contours can be summarized as follows:
  - Given an image, where we want to detect an existing object, we search for the object in the image I, by deforming a contour C in the direction that minimizes a generalized energy functional E (Kass et al., 1988).
  - When the deforming contour delineates the object, which lies in its interior, this energy functional should be at a minimum, so that the contour locks on the object.
  - Beginning from any starting point, subject to certain constraints, a snake will deform progressively into alignment with the nearest salient feature in a digital image.
  - Snakes thus provide a low-level mechanism that seeks appropriate local minima rather than searching for a global solution.

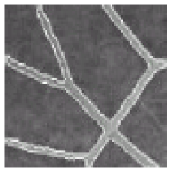
Snake Applications in the Biomedical Domain



MRI Salient objects Segmentation



Speech Reading



Blood Vessels Segmentation

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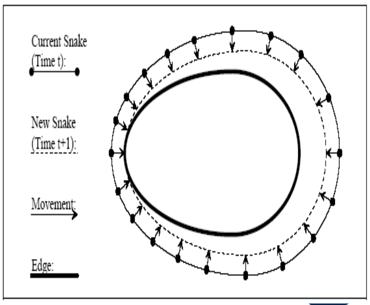
Snake as a parametric curve

- Geometrically, a snake is a parametric curve c, that deforms over a series of iterations
- The desired contour is given by minimizing a function:

$$E^*_{snake} = \int_0^1 E_{snake}(v(s))\,ds = \int_0^1 E_{int}(v(s)) + E_{image}(v(s)) + E_{con}(v(s))\,ds$$

- where,
  - E_{int} = internal energy of the spline due to bending
  - E_{image}= image forces
  - E_{con}= external constraint forces
- Internal forces (give the model tension and stiffness), image forces (are used to drive the model towards salient features such as light and dark regions, edges, and terminations) mostly based on the gradient operator, and external forces (come from high-level sources such as human operators or automatic initialisation procedures)



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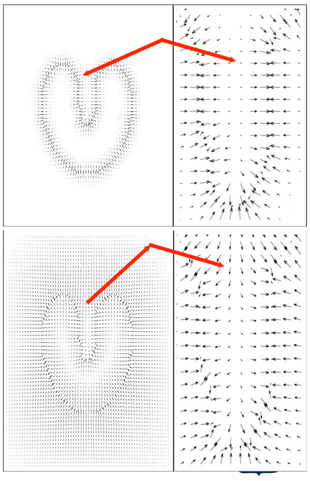
Shortcomings of the snake Kass model for the skin images and the GVF model

- The force field generated by the gradient operator fails on skin images, because :
  - gradient operator has large magnitude only in the immediate vicinity of the edges.
  - in homogeneous regions where the image is nearly constant, is nearly zero.
- The gradient vector flow (GVF) was originally introduced by Xu and Prince (1998) is defined so that minimizes the energy functional:

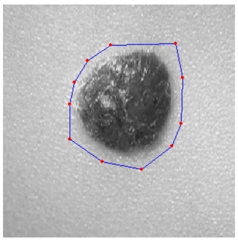
$$E = \iint \left[\mu \left(u_x^2 + u_y^2 + \upsilon_x^2 + \upsilon_y^2 \right) + \left| \nabla f \right|^2 \left| \vec{v} - \nabla f \right|^2 \right] dx\,dy$$

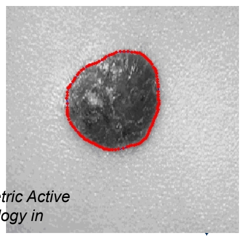
- The introduction of the GVF instead of the gradient force provides two great advantages:
  - the convergence of the snake into concavities and
  - a less sensibility to the initial.



The segmentation procedure

- Three main steps are executed.
  - Step 1 (initial contour): An initial contour suggestion is given as input to the snake model. The user enters at least three non-linear points to create an initial contour. In the example in Figure one closed contour is suggested, with eleven control points each. More control points are created automatically.
  - Step 2 (noise removal and parameters definition): Image is smoothed with a Gaussian filter to remove the undesirable noise. At this stage the user enters also the parameters related with the model's internal and external forces (alpha, beta, etc).
  - Step 3 (the contour evolution): The iterative algorithm proceeds (according to the set parameters) until it eventually gives a stable contour or until the user interrupts the iteration. In Figure, the contour is shown after 30 iterations.





I. Maglogiannis "Detection of Irregular Edges in Skin Lesions Using Parametric Active Contours for Dermatological Digital Images" Journal on Information Technology in Healthcare 5(2): 97–104, 2007

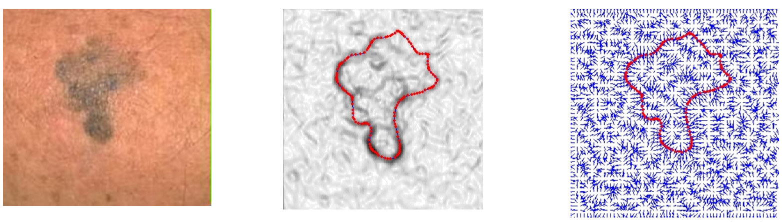
The active contour model parameters

- The <u>elasticity</u> parameter, known as the property *alpha* in literature, refers to the elasticity force, which acts to keep the curve from stretching.
- The <u>rigidity</u>, known as the property *beta,* handles the rigidity force, which acts to keep the curve from bending too much, as, for example, when turning a corner.
- The <u>viscosity</u>, known as the property *gamma* controls how quickly and how far the curve can be deformed between iterations.
- The <u>external force</u> parameter, known as *kappa,* has a default value of 1.25. Larger values cause a stronger force toward the image edges.
- <u>Delta Min/Delta Max</u>: As the curve is deformed, points are either added to the curve or subtracted from it. These factors determine the minimum and maximum pixel distance between adjacent points in the curve. If two adjacent points are further apart than the maximum, a point is added between them. If two adjacent points are closer together than the minimum, then one of the points is eliminated.
- <u>Contour Iterations</u>: This is the number of times the active contour is deformed according to the internal and external force fields and then “processed” by the algorithm to obtain the next starting contour location.

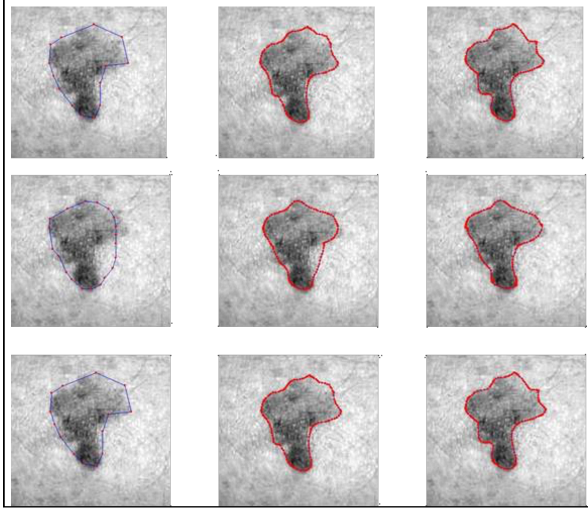
Experimental results (I)

- A data set of more than 50 skin images was examined, displaying 8 categories of skin lesions (junctional nevus, compound nevus, dysplastic nevus, non diagnostic nevus, Verruca Seborrhoica, melanoma and ceratoid nevus).
- The algorithm was tested on images with control points placed in the vicinity of the lesion.
- The following values for the parameters were found that they optimized performance: **alpha=0.2, beta=0.25, gamma=1, kappa=1.25, delta min= 0.25, delta max=5.5, sigma=1 for Gaussian Filter and μ=0.1 for the GVF**.

a b c



Experimental results (II)



Various experiments conducted showing the initialization, progression and the final configuration of the GVF snake with a different initial position and altering the values of the parameters.

In the 2nd row the final snake did not manage to enter the object concavity (down-left concavity of the melanoma), because the initial control points are set not so close to the real boundary.

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Conclusions

- The segmentation procedure using the implemented model results in estimating successively the optimal position of contour model for the majority of the images.
- The model was fast and exhibited good convergences properties.
- The model seems however to be sensitive to the initial contour positioning and failed to detect border concavities, when the control points are set not so close to the real boundary.
- Hence, a more robust and efficient active contour model for completely unsupervised segmentation of dermatological images is foreseen as future work.

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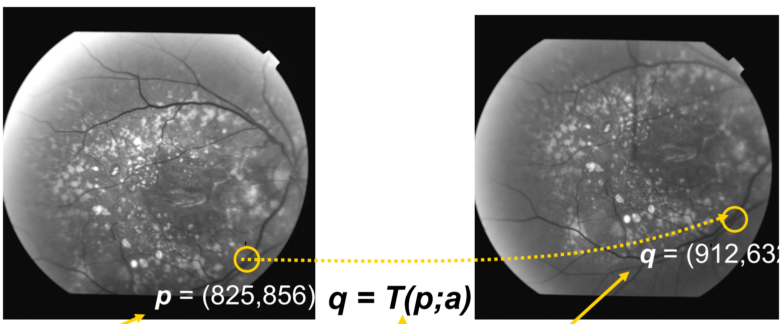
Image Registration

- Finding correspondence between two different images in order to correct transpositions caused by changes in camera position
- Factors
  - Magnification
  - Rotation
  - Horizontal Shifting
  - Vertical Shifting
- Solution
  - Selection of an efficient similarity ctiterion
  - Selection of an iterativive optimization algorithm

Registration Problem Definition



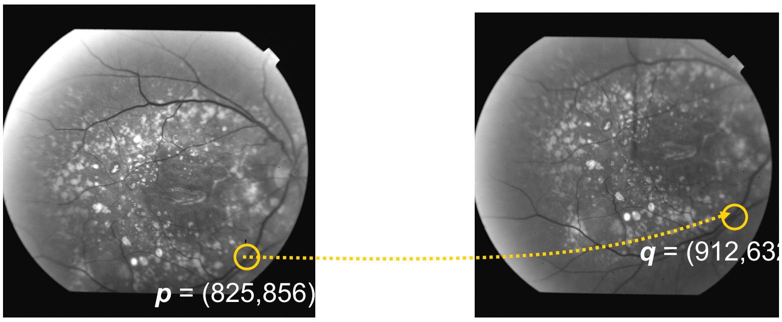
$q = T(p;a)$

Pixel location in first image

Homologous pixel location in second image

Pixel location mapping function

Example Mapping Function

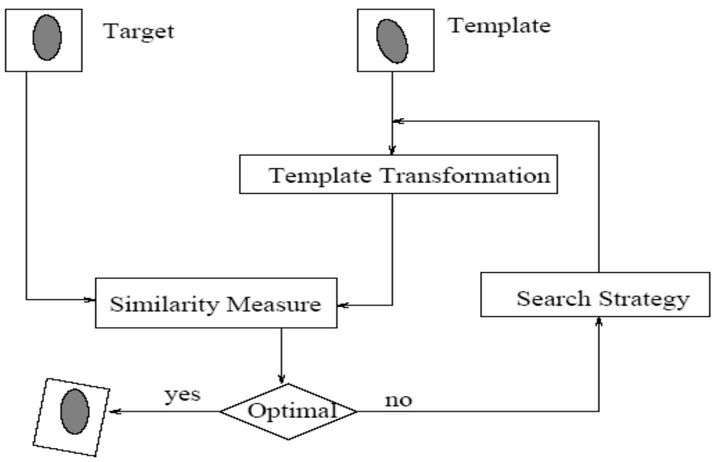


$$\mathbf{p} = (x, y)^T$$

$$\mathbf{\Theta} = (s, t_x, t_y)^T$$

$$\mathbf{T}(\mathbf{p}; \mathbf{\Theta}) = \begin{pmatrix} sx + t_x \\ sy + t_y \end{pmatrix}$$

Registration Algorithm



Magnification and Rotation

- Steps
  - Fourier Transform (independent of horizontal and vertical shifting)
  - Log-polar transform eliminates the dependency on magnification and rotation
  - Use of the cross-correlation function to find the scale factor and the rotation angle that maximizes the corresponding criterion

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I. Maglogiannis : "Automated Segmentation and Registration of Dermatological Images" Journal of Mathematical Modeling and Algorithms, vol. 2 pp. 277-294 Springer

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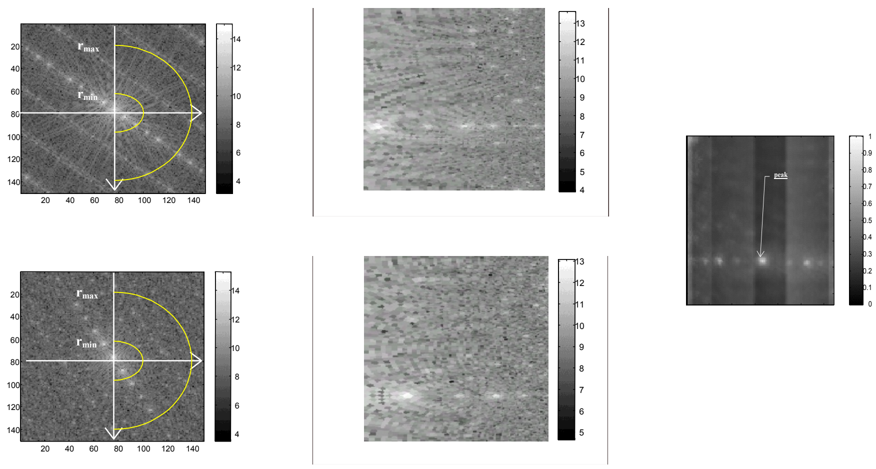
Example for M=0,8 and R=20°



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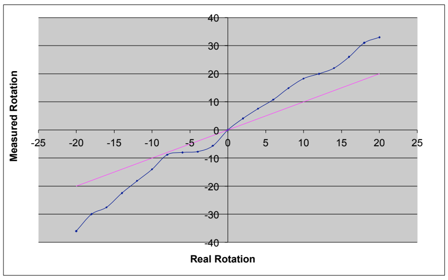
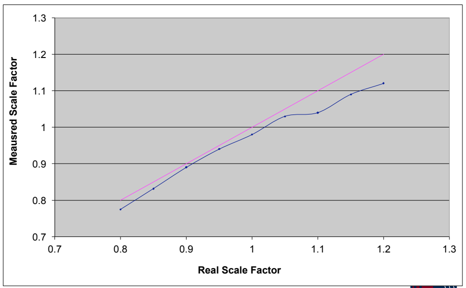
Accuracy of the log-polar Fourier transform in calculation of the rotation and scale factor





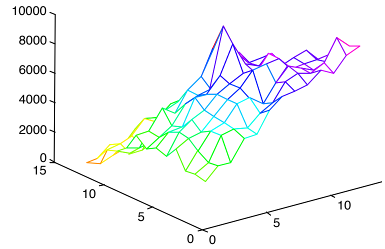
Vertical and Horizontal Shifting

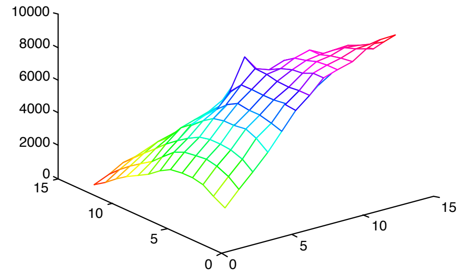
- Use of exhaustive algorithms - Similarity Criteria
  - Conventional
    - Correlation Function
    - Correlation Coefficient
    - Sum of absolute values of the differences
    - Mean Ssquare Value of the differences

$$\gamma(s,t)=\frac{\sum_x\sum_y[f(x,y)-\overline{f(x,y)}][w(x-s,y-t)-\overline{w}]}{\left\{\sum_x\sum_y[f(x,y)-\overline{f(x,y)}]^2\sum_x\sum_y[w(x-s,y-t)-\overline{w}]^2\right\}^{1/2}}$$

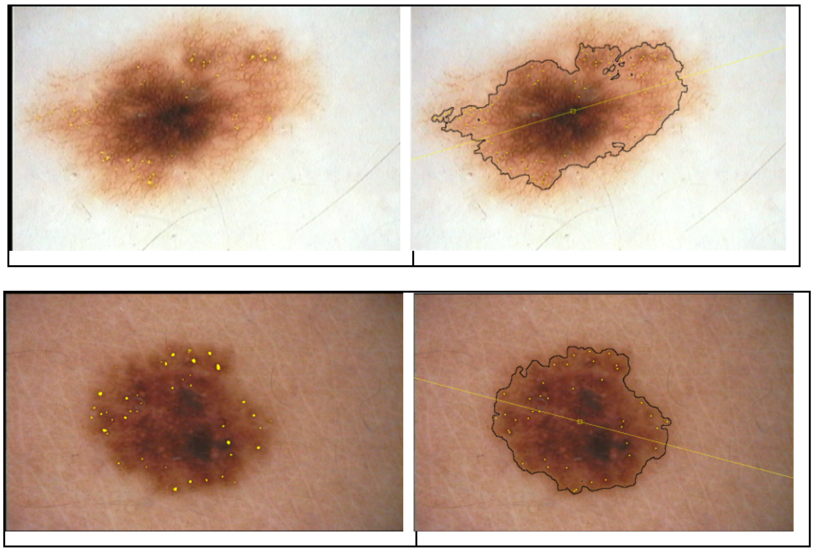
  - Non Conventional
    - Sign Change Criterion (Number of sign changes in the image of differences)
  - SCC better results for higly and medium altered images
  - MSV for low altered images
- Use of intelligent methods – Simulated Annealing

Typical behavior of the similarity criteria in high altered images

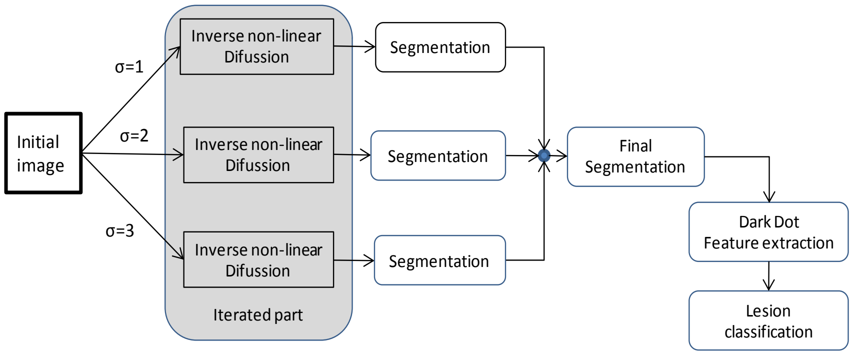




Detection of Globules in Skin Images

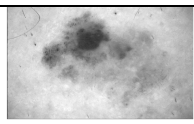


The graphical outline of the algorithm

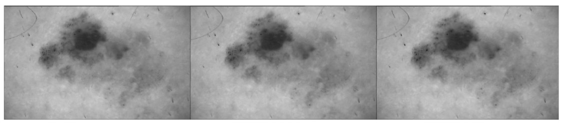


I. Maglogiannis, K. K. Delibasis, "Enhancing classification accuracy utilizing globules and dots features in digital dermoscopy", Computer Methods and Programs in Biomedicine Elsevier Vo. 118, Issue 2, Pages 124-133 (2015)

The intermediate steps of dot segmentation for an exemplar dermoscopy image

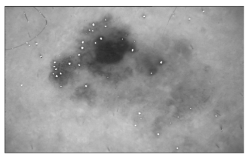


(a) Initial image in greyscale



(b) Image with enhanced dark circular structures for σ=1, 2, 3

(c) the response image with enhanced dark circular structures for σ=1, 2, 3



(d) the final segmentation of the dots, superimposed on the initial dermoscopy image.

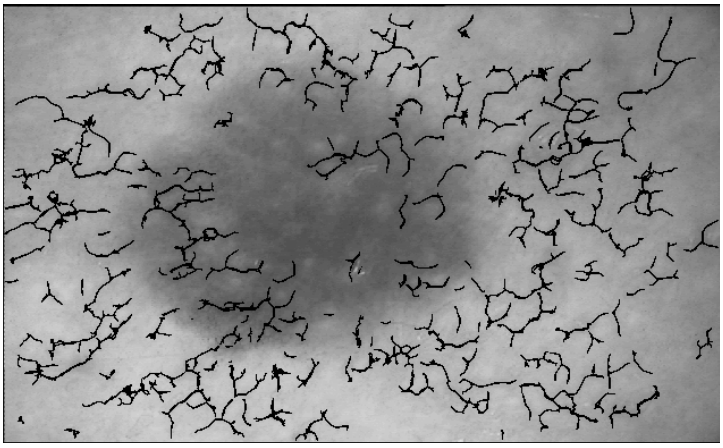
Results

Images	Number of Dots				Sensitivity
	Segmented	Segmented correctly	Missed (FN)	FP	%
Non-Maligant	2544	2512	105	32	95.98
Malignant	1164	1032	98	132	91.17

	Confusion Matrix	Sensitivity Specificity Accuracy
Without Dot Features	40 10 / 6 48	0.8696 0.8276 0.8462
With Dot Features	46 4 / 6 48	0.8846 0.9231 0.9038

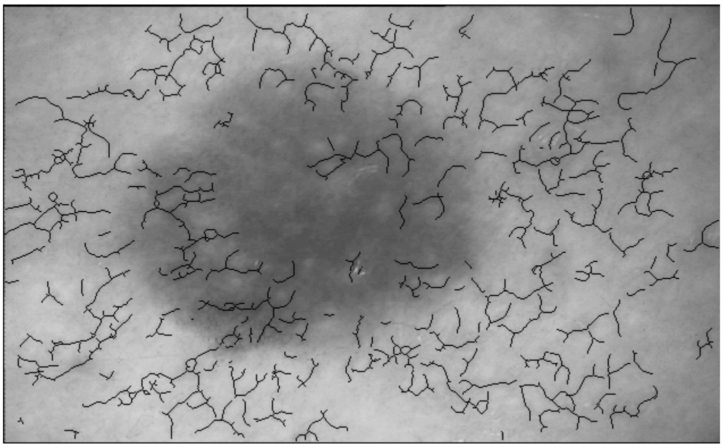
	Confusion Matrix	Sensitivity Specificity Accuracy
Multilayer Perceptron	36 14 / 12 42	0.7500 0.7500 0.7500
kNN, k=1	38 12 / 16 38	0.7037 0.7600 0.7308
Random Forest	36 14 / 22 32	0.6207 0.6957 0.6538
SVM polykernel c=5	36 14 / 10 44	0.7826 0.7586 0.7692
SVM puk kernel	36 14 / 16 36	0.6923 0.7308 0.7115

Detection of Streaks - Segmented linear structures (black pixels)

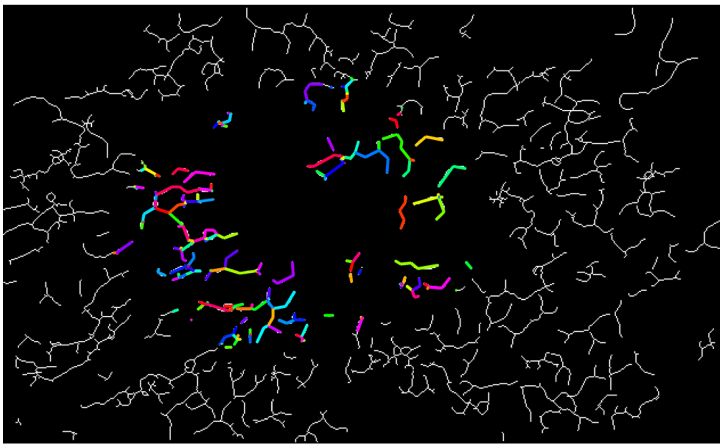


K. Delibasis, K. Kottari, I. Maglogiannis Automated Detection of Streaks in Dermoscopy Images. AIAI 2015: 45-60

Thinning / medial axis of previous image



Labeled linear structures that lie inside the lesion shown in color

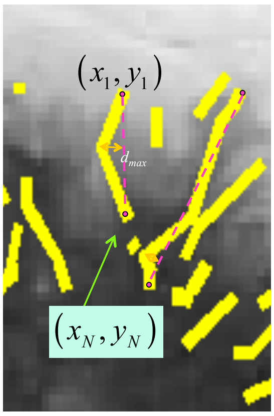


Criteria for streak selection

- have low curvature
- “co-radially oriented in the boundary”,
- “darker than their neighborhood”,
- “shorter than the 1/3 of the minor axis of the lesion” and longer than one percent of the major axis”

Crietria according to
Sadeghi, M., Lee, T. K., McLean, D., Harvey Lui, Atkins, M. S.: Oriented Pattern Analysis for Streak Detection in Dermoscopy Images. In: N. Ayache et al. (Eds.): MICCAI 2012, Part I, LNCS 7510, pp. 298–306 (2012)

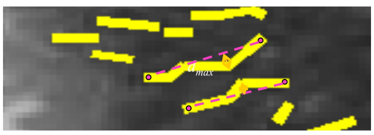
Low Curvature Criterion



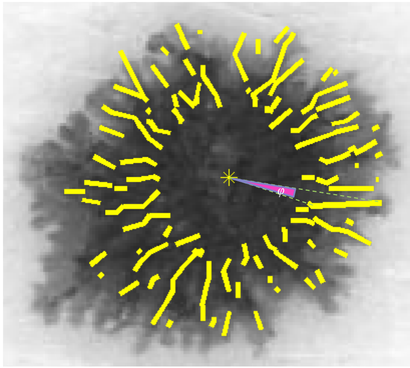
$$d_i = |x_i \delta y + y_i \delta x - C|, C = y_N x_1 - y_1 x_N$$

$$d_{\max} = \max(d_i)$$

$d_{max} < tol$



Radial orientation Criterion



φ: Apparent angle of streak from the center of lesion
A linear structure with $\varphi > \varphi_{tol}$ is rejected

$$\varphi = \left| \tan^{-1}\frac{y_n}{x_n} - \tan^{-1}\frac{y_1}{x_1} \right|$$

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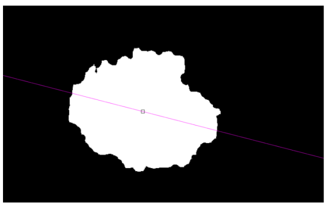
Length Criterion

- The length of the major and minor axis of the lesion L_1, L_2 is calculated using the moments of inertia of the 2nd order
- The following should be satisfied for each streak with length L:



$$L > \frac{1}{3}L_2 \; OR \; L < 0.01L_2, L = \sqrt{(x_1 - x_N)^2 + (y_N - y_1)^2}$$

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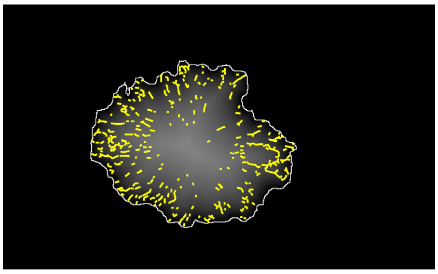
Proximity to boundary Criterion

- Streaks appear close to the boundary of the lesion.
- the distance transform (DT) of the binary lesion is calculated.
- A linear structure is discarded if

$$\max\left(DT\left(x_1,y_1\right),DT\left(x_N,y_N\right)\right) > \frac{1}{3}L_2$$

- L_2 : length of lesion minor axis.



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Streak-based features

- Number of
  - Individual detected streaks,
  - Pixels in streaks
- Asymmetry of azimuthial angle and radial distribution of streaks (A_θ, A_r)
  - The centroid of each streak $\mathbf{c}_i$ is located, defined as its median pixel.
  - The azimuthial angle of the centroid θ_i and its distance from the boundary r_i =DT($\mathbf{c}_i$) is calculated for each streak i=1,2,…,K.
  - The histogram of θ_i and r_i is calculated (H_θ and H_r respectively) using 10 bins

$$A_\theta = \frac{\max\left(H_\theta\right)-\min\left(H_\theta\right)}{\max\left(H_\theta\right)}, A_r = \frac{\max\left(H_r\right)-\min\left(H_r\right)}{\max\left(H_r\right)}$$

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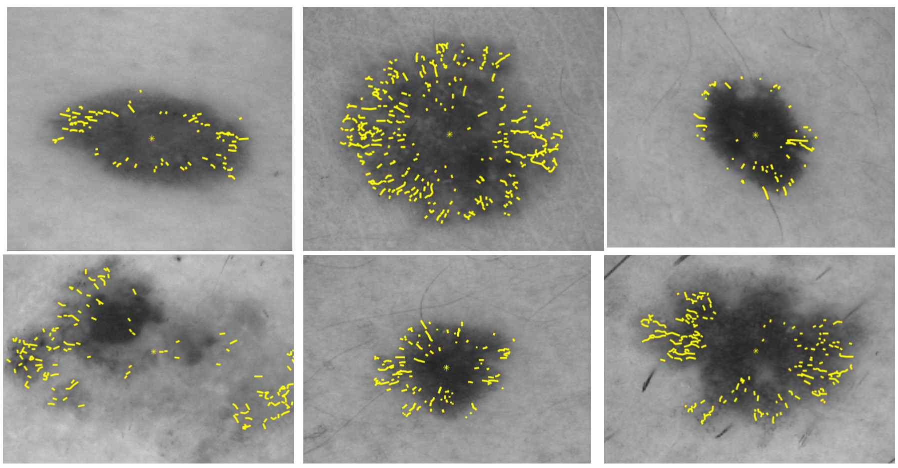
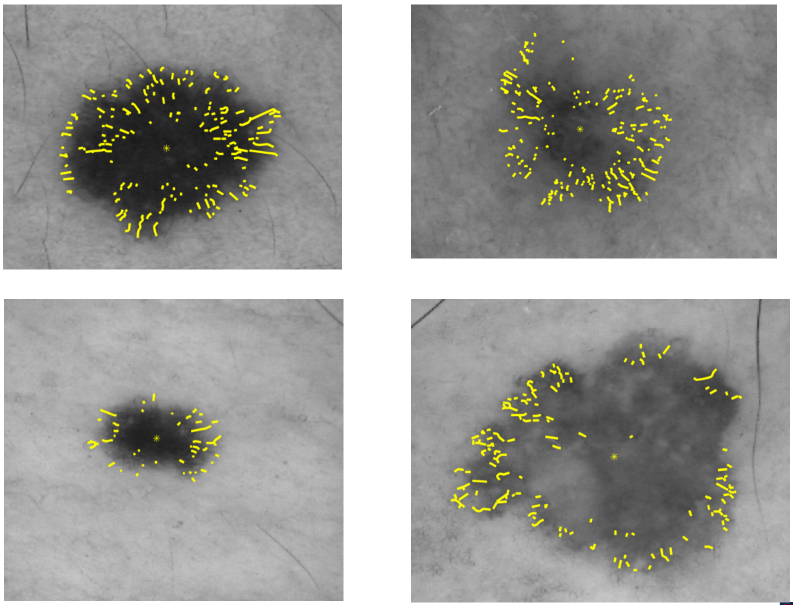
Experimental Dataset

- 99 images acquired by the ELM Molemax II device at Hospital of Wien and the Dept. of Plastic Surgery and Dermatology, General Hospital of Athens G. Gennimatas
  - 64 images with non-malignant lesions and
  - 35 images with malignant lesions, determined by histological analysis.
- Image size of 632 × 387 pixels, with 0.05 mm/pixel spatial resolution.
- Lesions manually delineated.
- Algorithmic Parameters used : d_{max} =2 pixels, φ_{tol} =2 deg, TH=0.1, TL=0.01 (with respect to maximum λ_{max} value).
- σ takes integer values of 1, 2 and 3



Exemplar results



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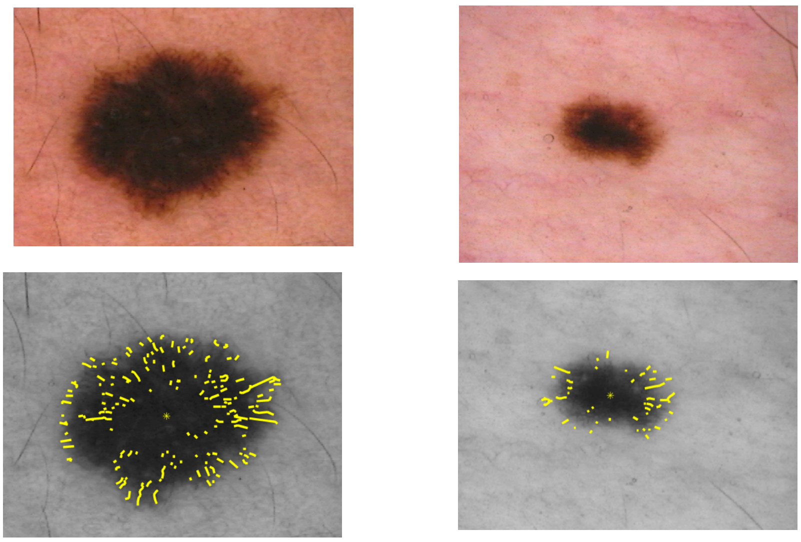

Exemplar results

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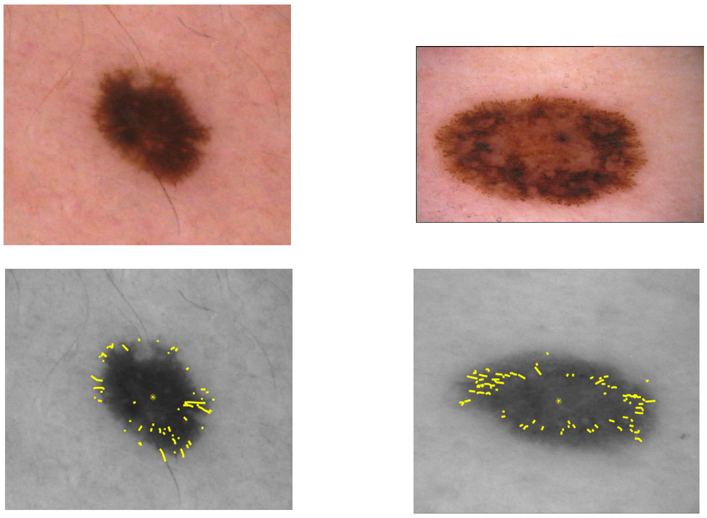

Exemplar results

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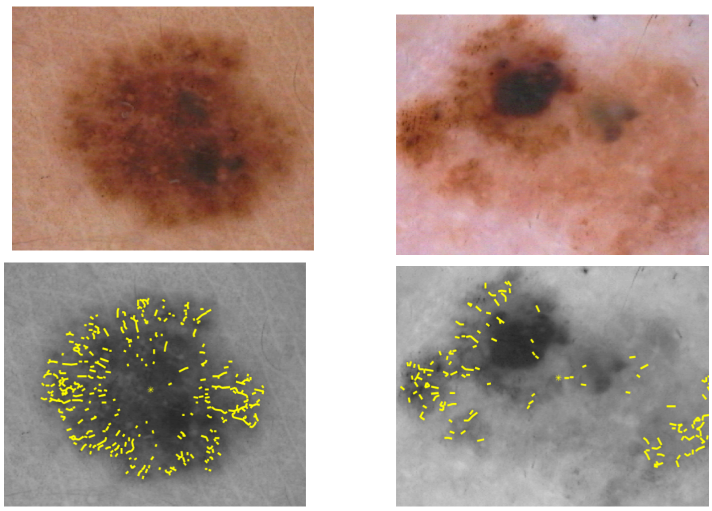

Exemplar results

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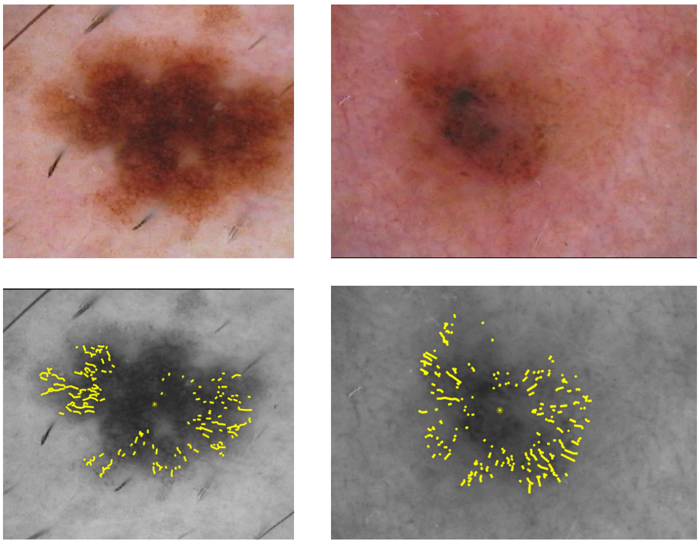

Exemplar results

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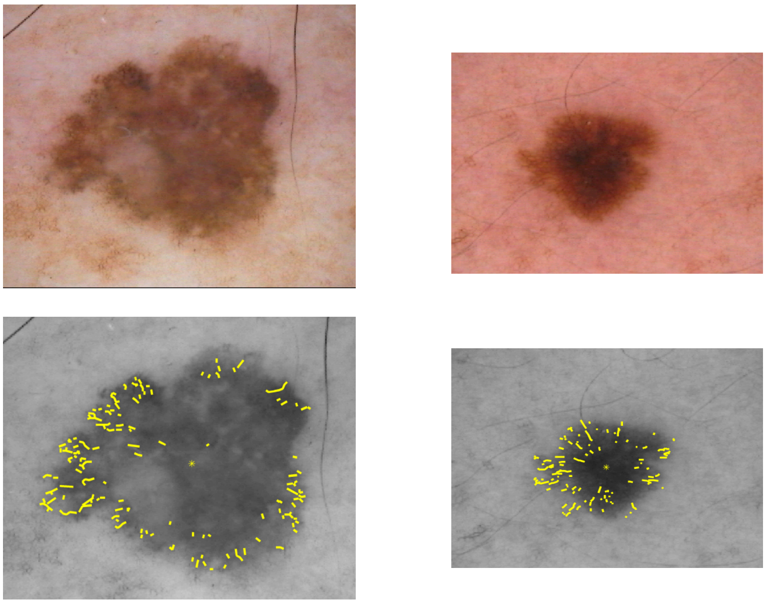

Exemplar results

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Classifiers

- Statistical
  - Covariance matrices are computed for the discriminative measures. Parametric discriminant functions are then determined, allowing classification of unknown images.
- Decision Trees and Bayesian Networks
- Neural networks
  - They define non-linear decision surfaces
  - Back-propagation learning ability that alleviates the need for explicitly defining the parameters space.
- Support Vector Machines (SVMs)
  - An estimation algorithm that separates data in two classes.
  - Allow the expansion of the information provided by the total feature set as a linear combination of a subset of the data in the training set (support vectors). These vectors locate a hypersurface that separates the input data with a very good degree of generalization.

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SELECTED FEATURES

Feature	MM (std)	MD (std)	Feature	MM (std)	MD (std)
mean-R	116.65 (33.65)	157.29(28.09)	Complexity	10.89 (16.87)	8.07 (12.37)
I-mean	75.72 (22.04)	101.66 (22.32)	ASM	8949.96 (7505.5)	7247.92 (6716.8)
L-mean	141.86 (40.50)	190.46 (38.45)	Dissimilarity	3430017(2571071)	2781110(2571071)
mean-G	62.46 (19.60)	83.79(21.74)	Perimeter	2640.49 (1874.6)	2252.06(1592.4)
mean-B	48.03 (16.68)	63.90 (20.31)	Area	68924.59 (25955)	64009.45(23396)
GMSM-mean	140.25 (36.11)	134.51 (32.18)	Eccentricity	1.68 (0.42)	1.77(0.48)
S-mean	93.48 (22.91)	100.56 (18.74)	Asymmetry	30.53 (18.63)	29.68 (16.99)
H-mean	27.66 (22.06)	25.96 (28.56)	Grad-mean	1.26 (0.52)	1.23 (0.45)
B-mean	40.41 (5.48)	38.88 (4.44)	A-mean	98.8 (5.35)	100.52 (4.31)

Selected features for the construction of the training and test set, where MM and MD the mean values for the melanoma and the nevus cases respectively.

I. Maglogiannis, E. Zafiropoulos, C. Kyranoudis, "Intelligent Segmentation and Classification of Pigmented Skin Lesions in Dermatological Images" Advances in Artificial Intelligence: Lecture Notes in Computer Science Vol 3955 pp. 214 – 223 2006

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Performance of the SVM algorithm using the exponential radial basis function with various values of sigma

SIGMA	ERRORS	TP	TN	FP	FN	ACCURACY	SPECIFICITY	SENSITIVITY
7	85	63	893	79	6	91.84%	91.87%	91.30%
8	87	62	892	80	7	91.64%	91.77%	89.86%
6	88	62	891	81	7	91.55%	91.67%	89.86%
9	90	62	889	83	7	91.35%	91.46%	89.86%
10	91	62	888	84	7	91.26%	91.36%	89.86%
12	97	62	882	90	7	90.68%	90.74%	89.86%
5	99	61	881	91	8	90.49%	90.64%	88.41%

TP: True Positive (melanoma instances actually classified as melanoma by the SVM algorithm)

TN: True Negative (dysplastic nevus instances actually classified as nevus by the SVM algorithm)

FP: False Positive (melanoma instances classified as nevus by the SVM algorithm)

FN: False Negative (dysplastic nevus instances classified as melanoma by the SVM algorithm)

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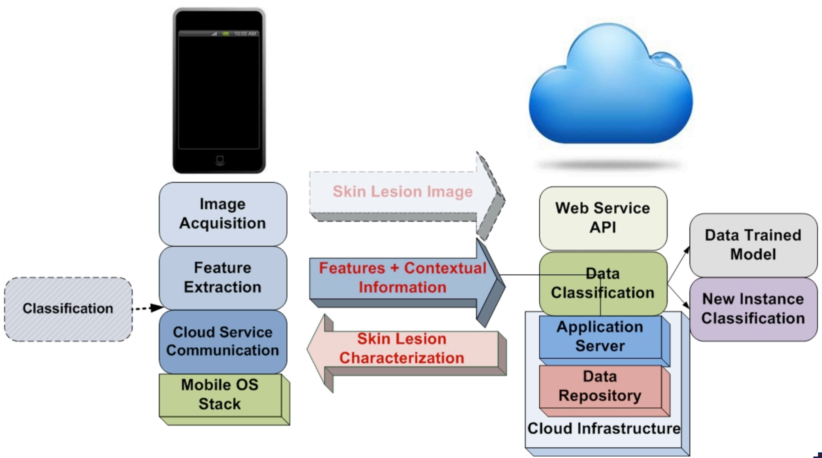
Mobile Implementation



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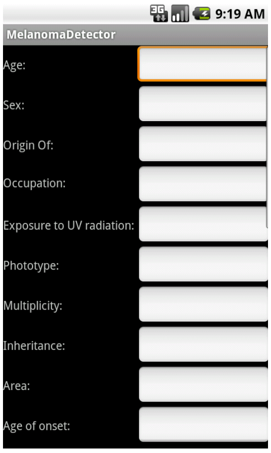
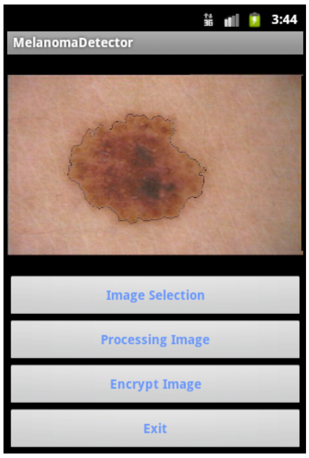
Screenshots of the Android mobile application. On the left: The initial screen for entering contextual data. On the right: A skin lesion image segmented by the mobile application.





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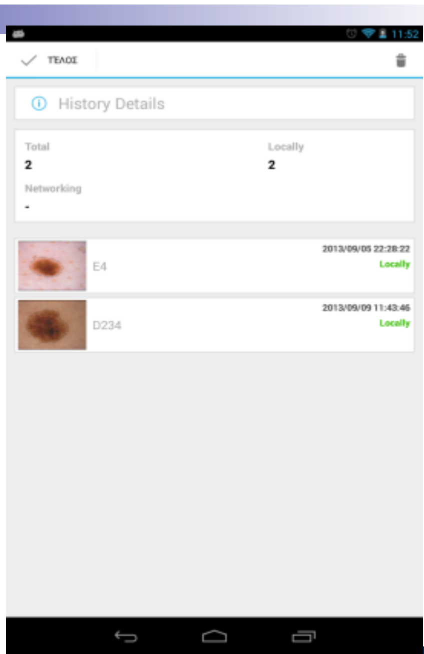
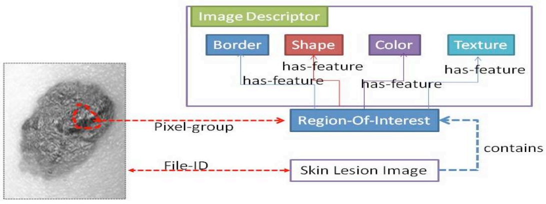
History Data

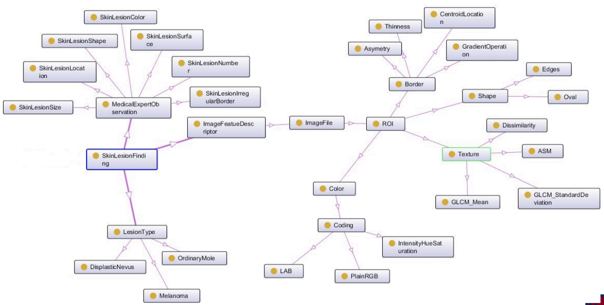


Artificial illumination sources and advanced lenses for better focus

C. Doukas, P. Stagkopoulos, I. Maglogiannis, "Skin lesions Image Analysis Utilizing Smart Phones and Cloud Platforms", Mobile Health Technologies Methods and Protocols Series: Methods in Molecular Biology, Vol. 1256 Rasooly, Avraham, Herold, Keith (Eds.) Springer 2015

Ontological modelling and taxonomy





Inference Logic

- Lesions in Melanoma class (meanR < 140) are less erythematic than Dysplastic Nevus Lesions (meanR > 150).
- The ASM value is significantly higher in melanoma images (ASM>3000) in comparison with Dysplastic Nevus (ASM<3000).
- The standard deviation of the Hue value which is higher for melanomas (H-std>14). This fact is corresponding to the colour variegation inside the border lesion, which is lower for non-malignant cases (H-std<12).
- Melanoma lesions are also more concentrated around the centre, since the variance of the distance of the border lesion points from the centroid location is lower (distance-standard <20). The corresponding feature for Dysplastic Nevus Lesions is >25 in most cases.

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Description Logic

- The above remarks could be translated to the following DL statements:
  - RoI_Dysplastic_Nevus=… ∃hasmorphological_features.Color.Coding.RGB.hasErythema.hasMeanR≥*n* …∪…=…∃hasmorphological_features.Texture.hasASM<*m*… ∃hasmorphological_features.Border.Shape.hasCentroid_Distance≥*k*….=… ∃hasmorphological_features.Color.Coding.Intensity_Hue_Saturation.hasHue ≤*h*…
    - (n≈140, m≈3000, k≈25, h≈8)
  - RoI_Melanoma=… ∃hasmorphological_features.Color.Coding.RGB.hasErythema.hasMeanR≤*n’* …∪…=…∃hasmorphological_features.Texture.hasASM>*m’*… ∃hasmorphological_features.Border.Shape.hasCentroid_Distance<*k’*….=… ∃hasmorphological_features.Color.Coding.Intensity_Hue_Saturation.hasH≥*h ’*…
    - (n’≈150, m’≈3000, k’≈20, h’≈14)

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