Thermography

by: mahnaz Etehadtavakol

All objects  as a function of their temperature emit IR radiations

As an object gets hotter → more intense IR radiation

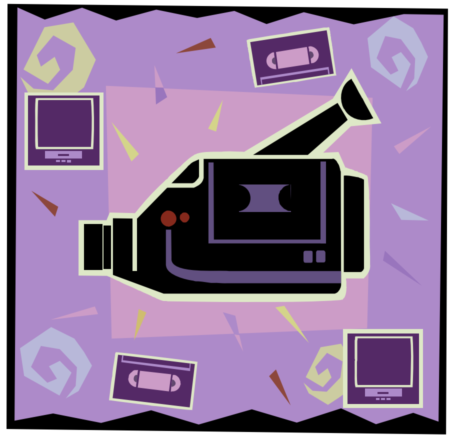
→ shorter wavelength

0.75 µm < IR < 300 µm

1 THZ< IR < 430 THZ

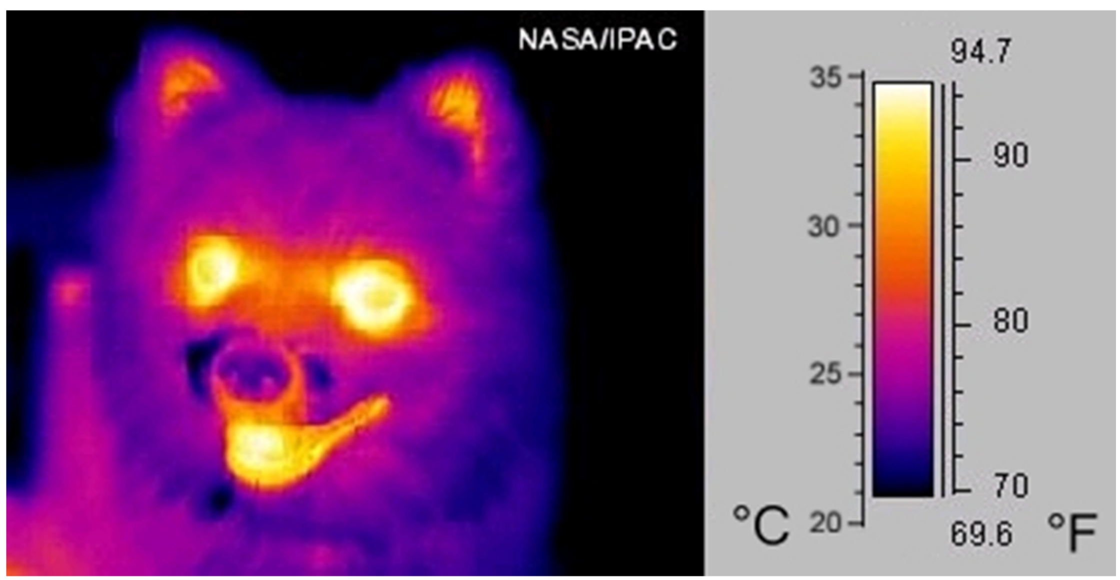
8 µm <  < 12 µm

Thermal imaging

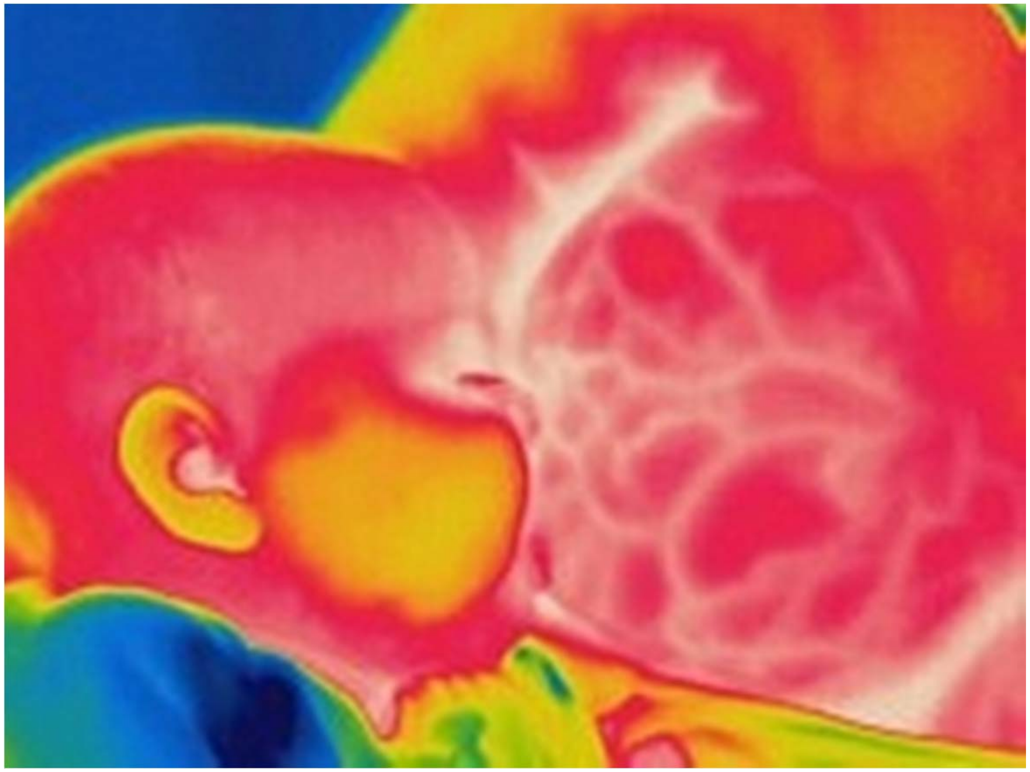


Can Detect

in the infrared range and produce thermograms



Thermography shows variations in temperature

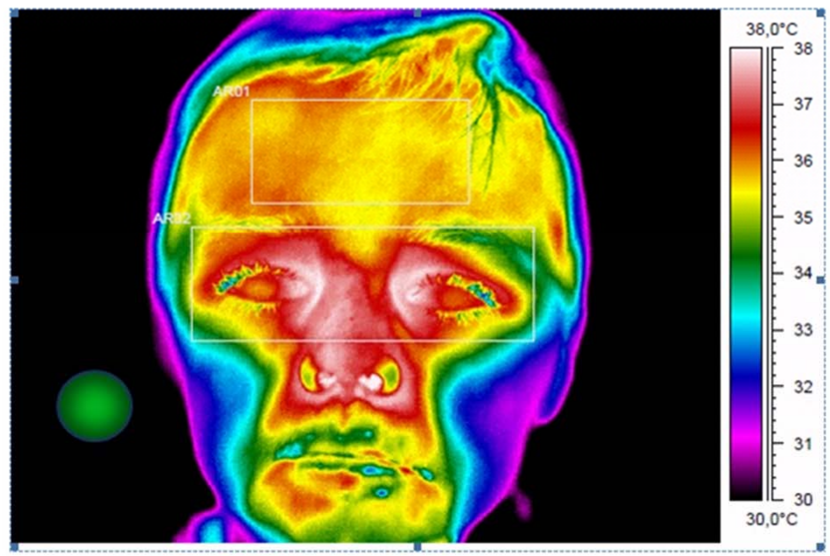


Airport personnel used thermography

suspected

cases

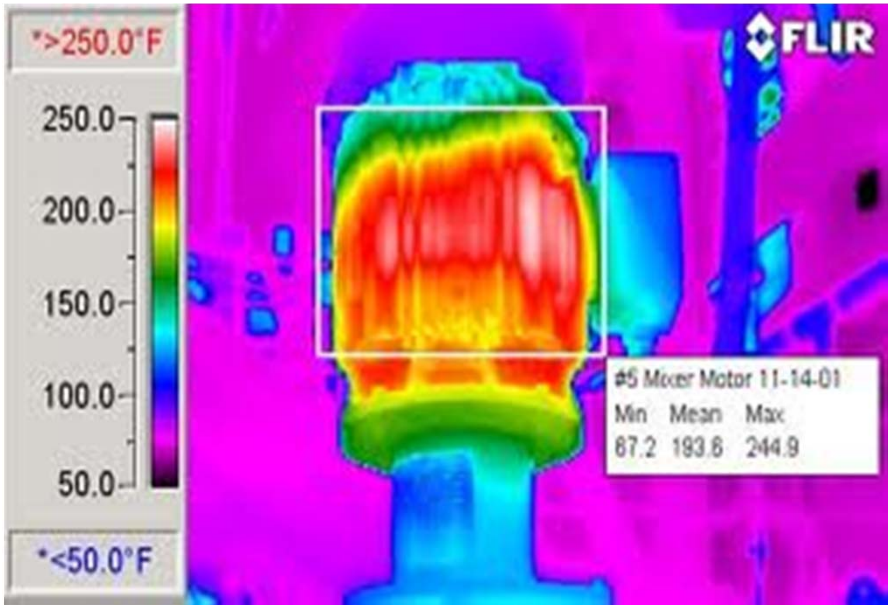
during the 2009 pandemic



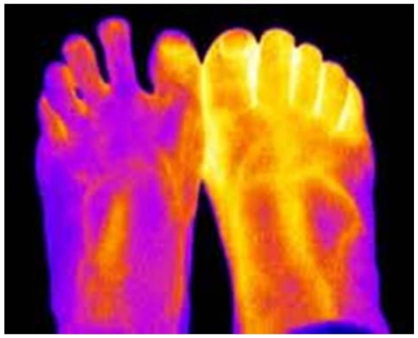
Subject 3 fever

Application of thermography

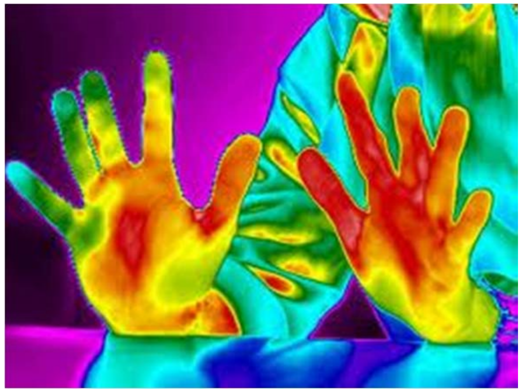
Fire rescue



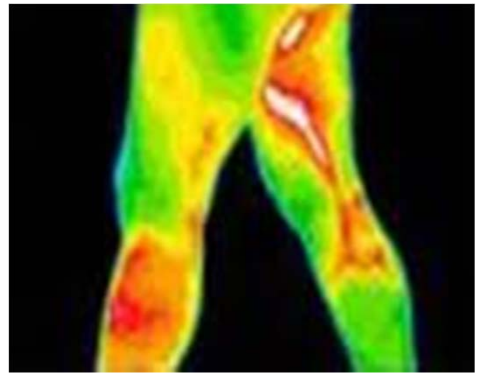
Motor inspection



Oncology-feet

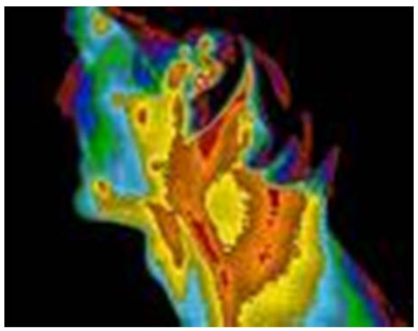


Multiple Sclerosis

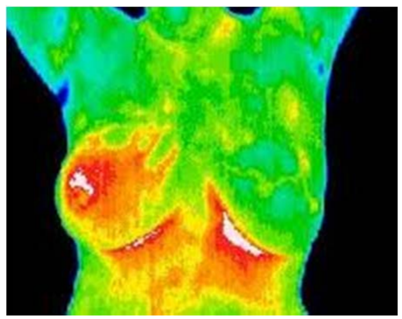


whiplash

Medical application

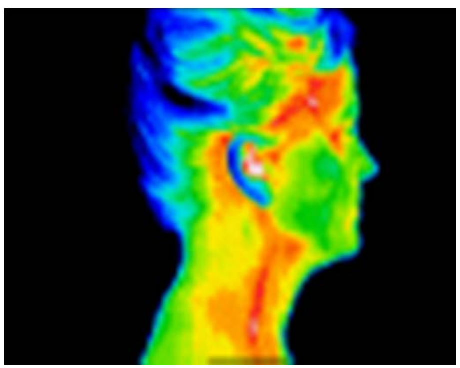


Pre stroke

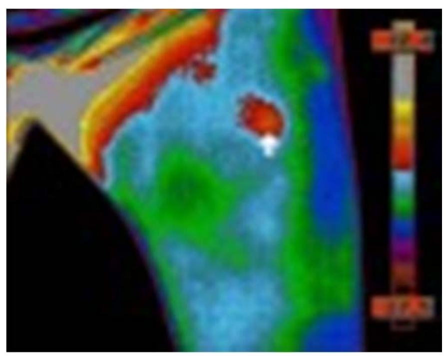


Breast cancer

Whole body



headache



Skin cancer

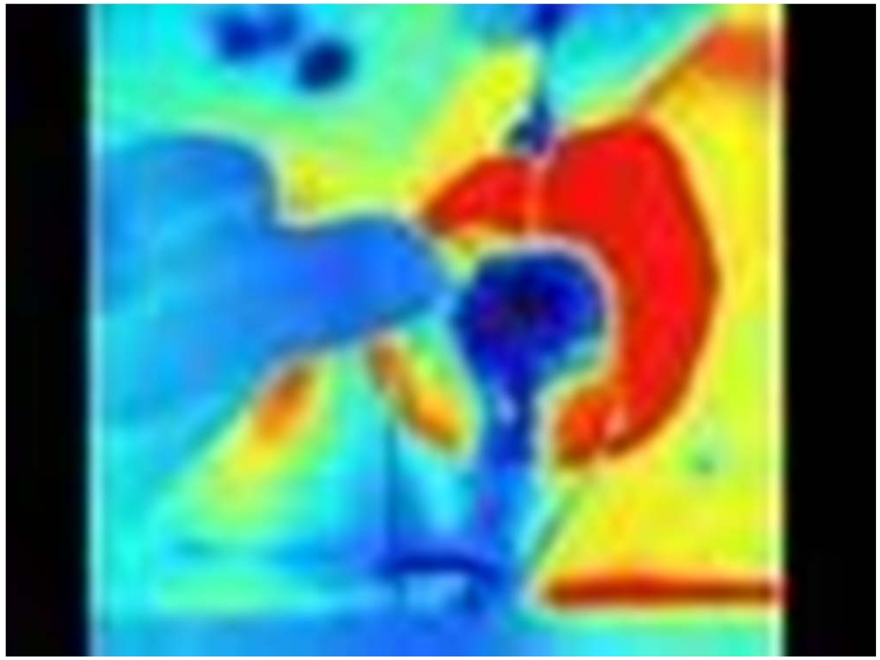
April 1989

SCIENTIFIC COMPUTING & AUTOMATION

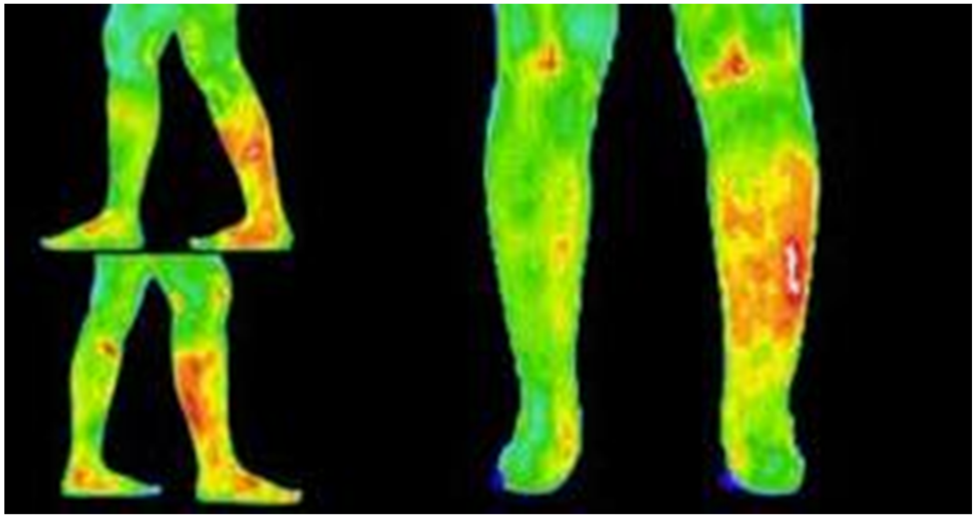
- Computerized Thermal Imagery
- Computational Chemistry in Research
- Experts Creating Expert Systems

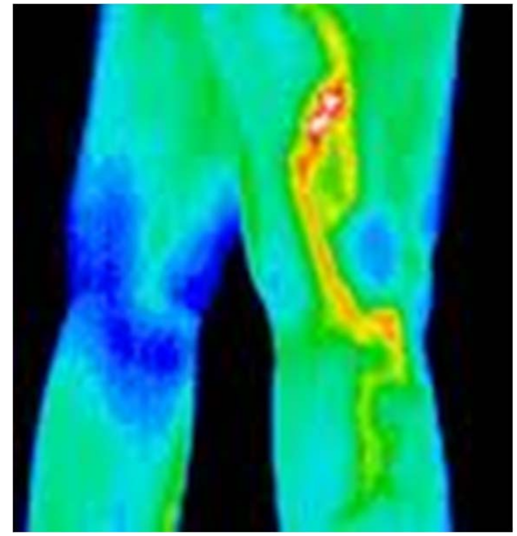
BUYER'S GUIDE
Data Acquisition & Control

PRODUCT PROFILE
Lab Integrators

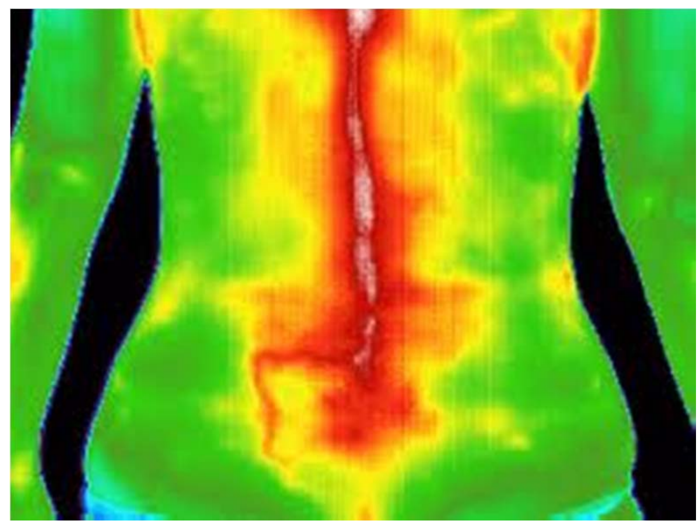


Thermography during surgery





Location of pain



Breast thermography

- early detection
- non-invasive
- non-radiating
- passive
- fast
- painless
- low cost
- risk free
- no contact with the body
- women with all ages
- all sizes of breast
- fibrocystic breasts
- dense tissue
- pregnant
- nursing women
- portability
- real time imaging
- monitoring after surgery

A normal breast thermogram for each woman is like her fingerprint

It’s uniquely hers,

and it doesn’t change much over time

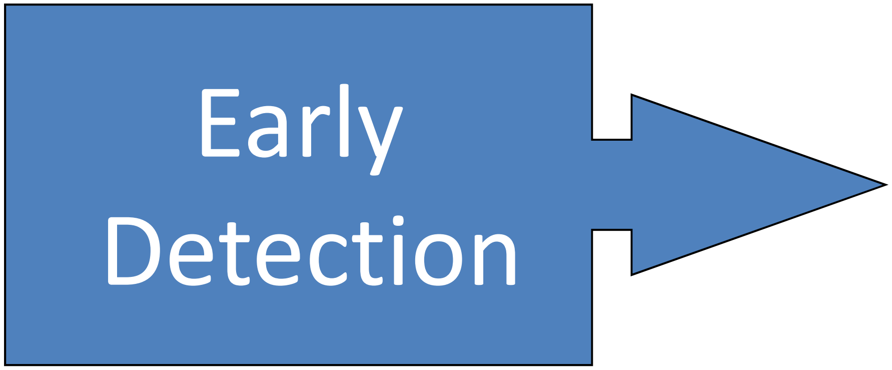
Thermography vs. Mammography

Thermography → Physiological changes

Mammography → Anatomical changes

Physiological changes → Anatomical changes

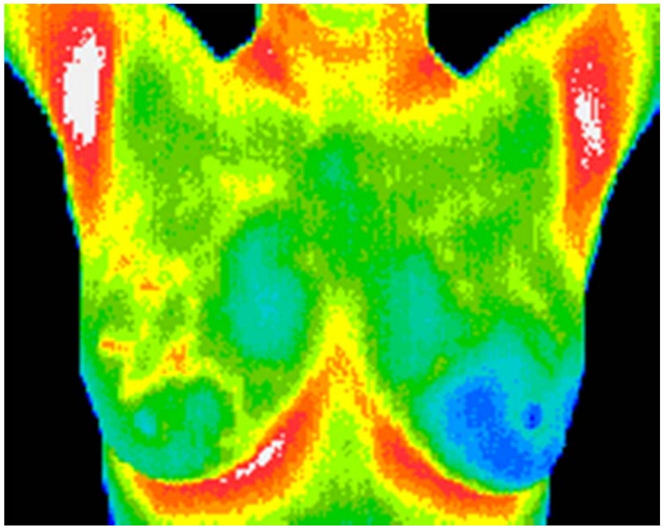
Thermography <u>complementary</u> Mammography



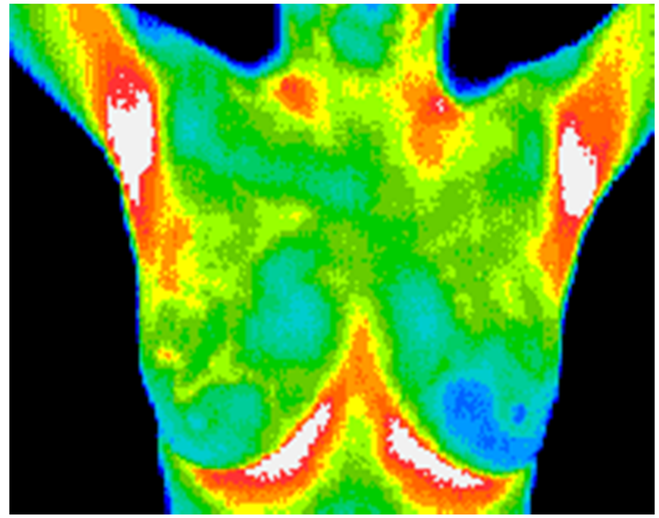
%85

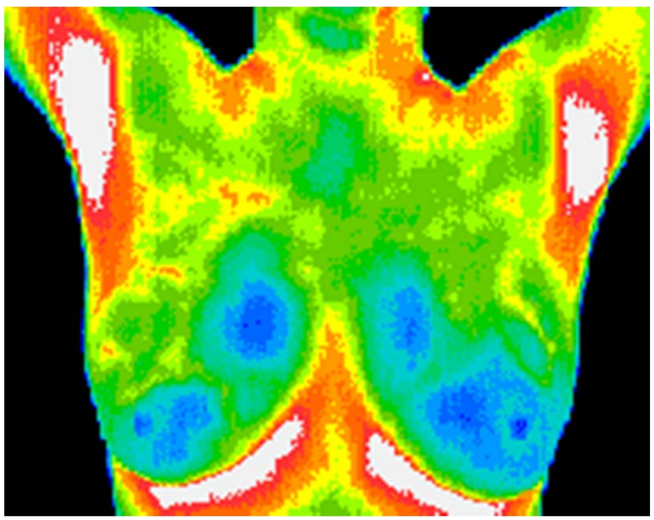
http://yourtotalhealth.ivillage.com/thermography.html
]www.earlycancerdetection.com/breast_thermo.html

Baseline

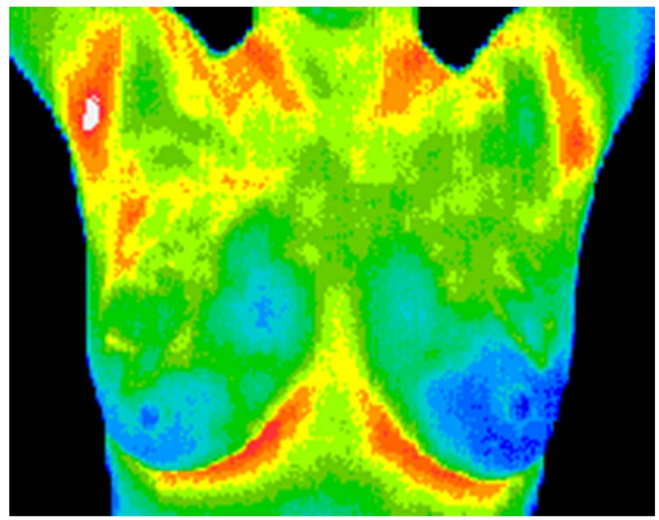


3 month follow up



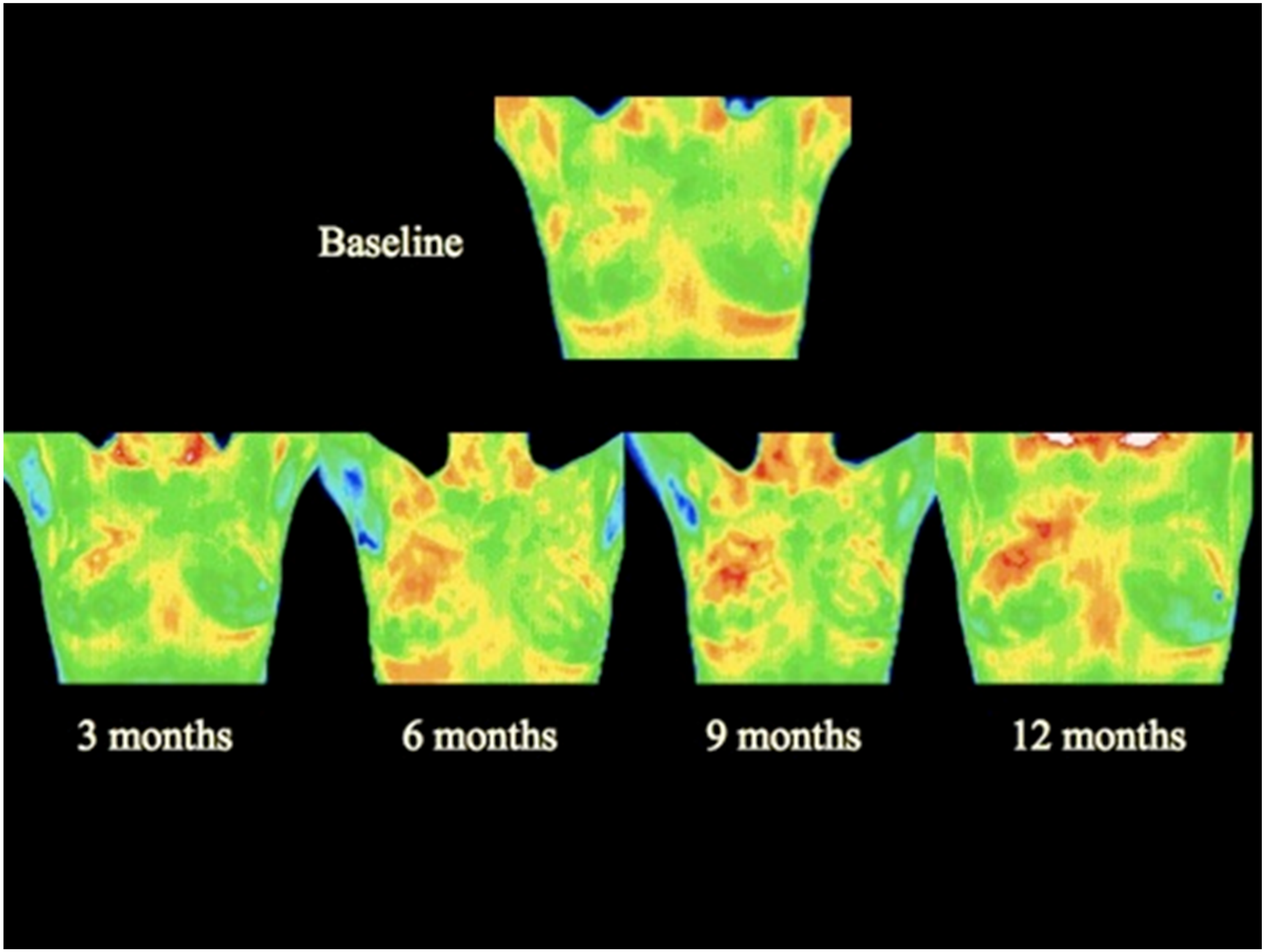


First annual



Second annual

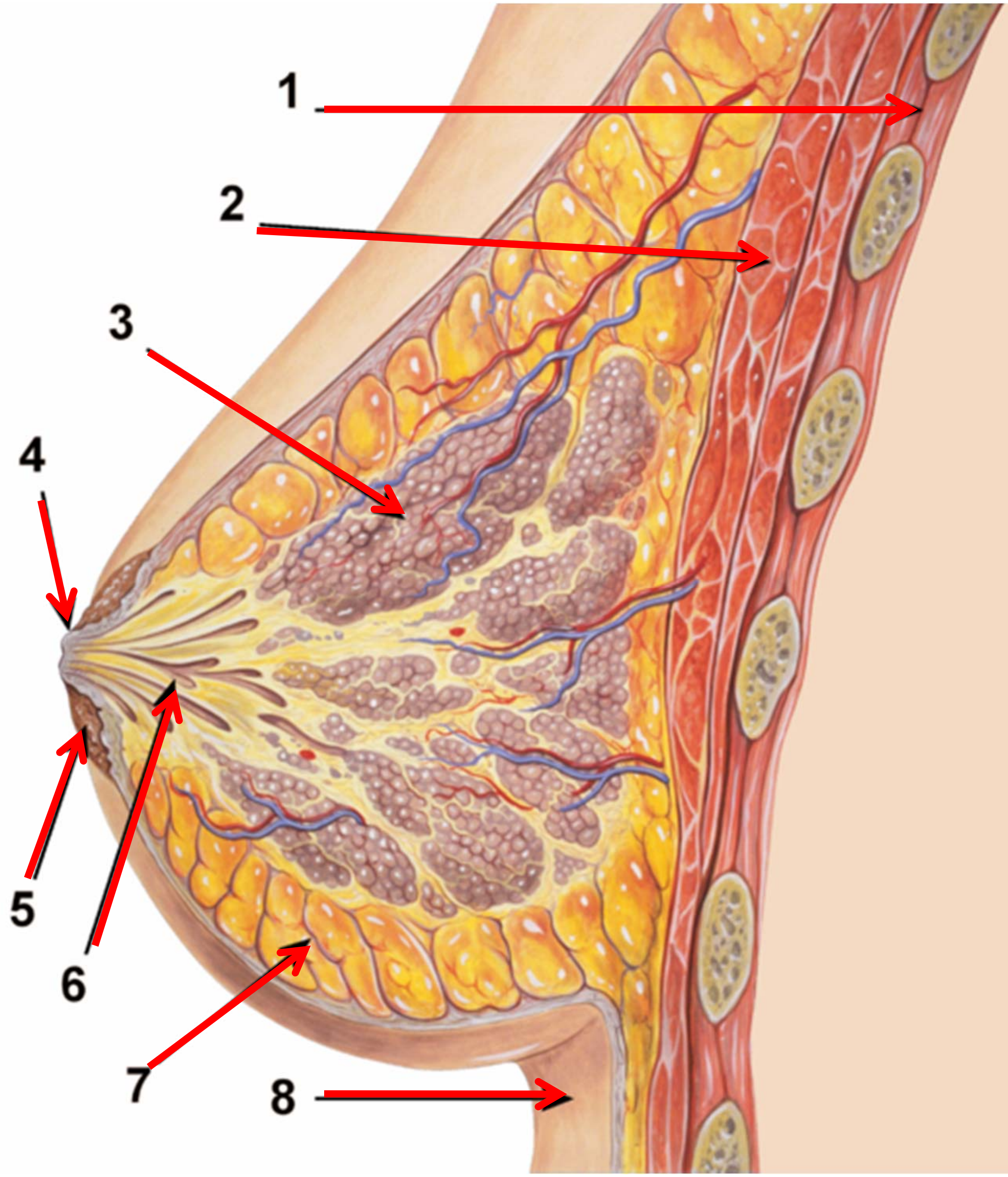
Healthy thermograms stable for two years



Ductal Carcinoma in Situ was not detectable by mammogram until final image

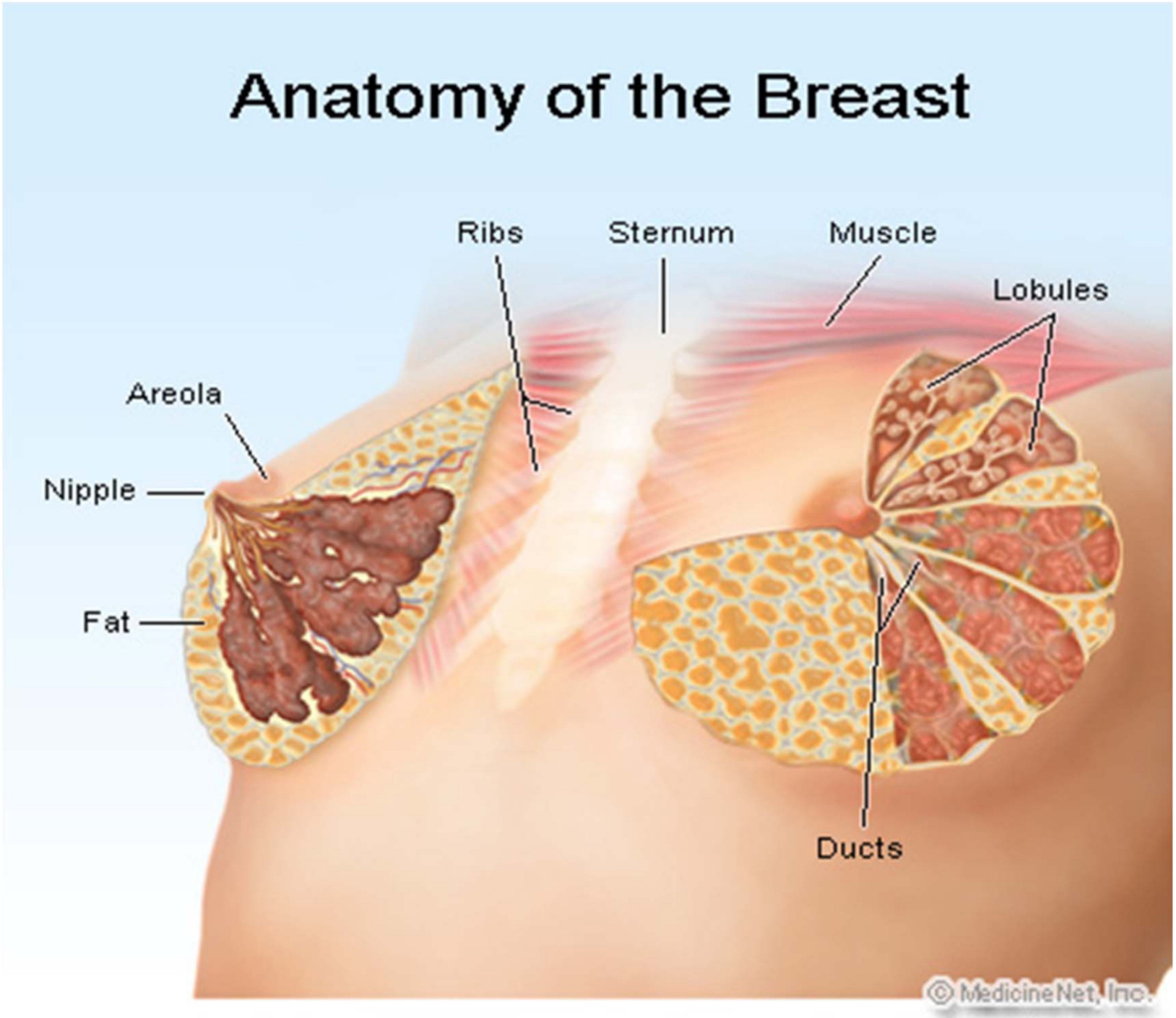
Breast thermography

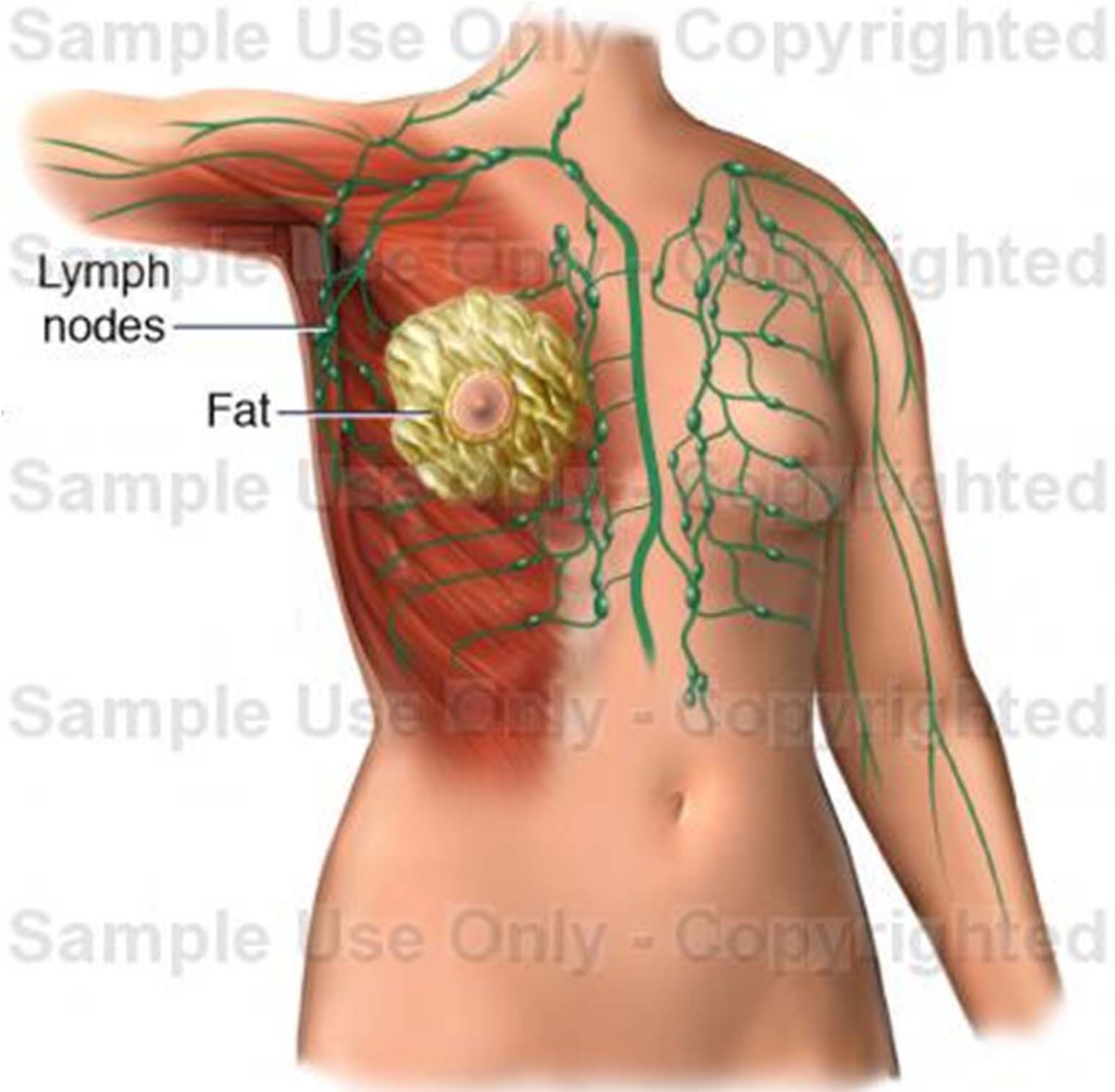
- In 1982 and again in 2005
- FDA
- breast thermography as an adjunctive breast screening

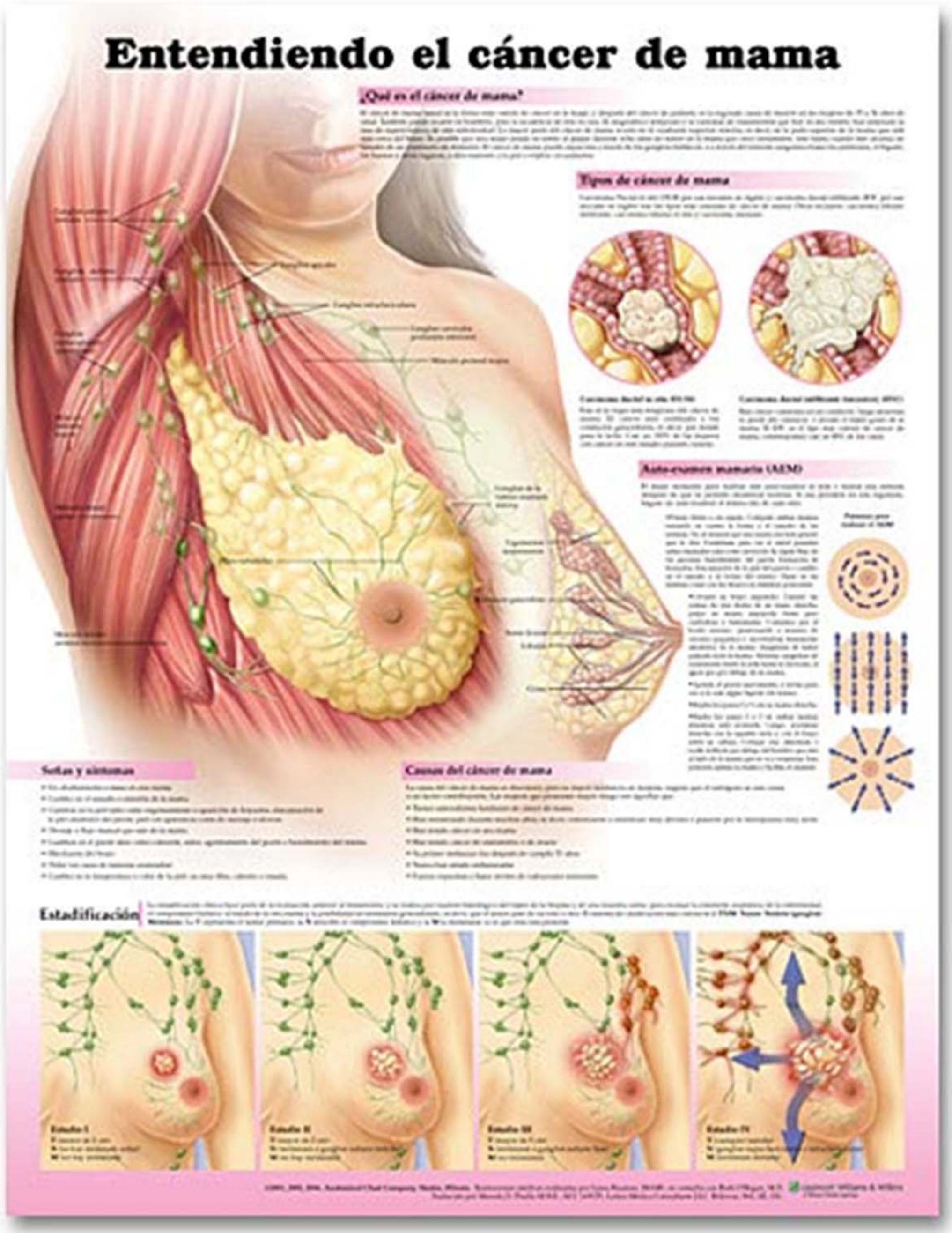


Breast anatomy

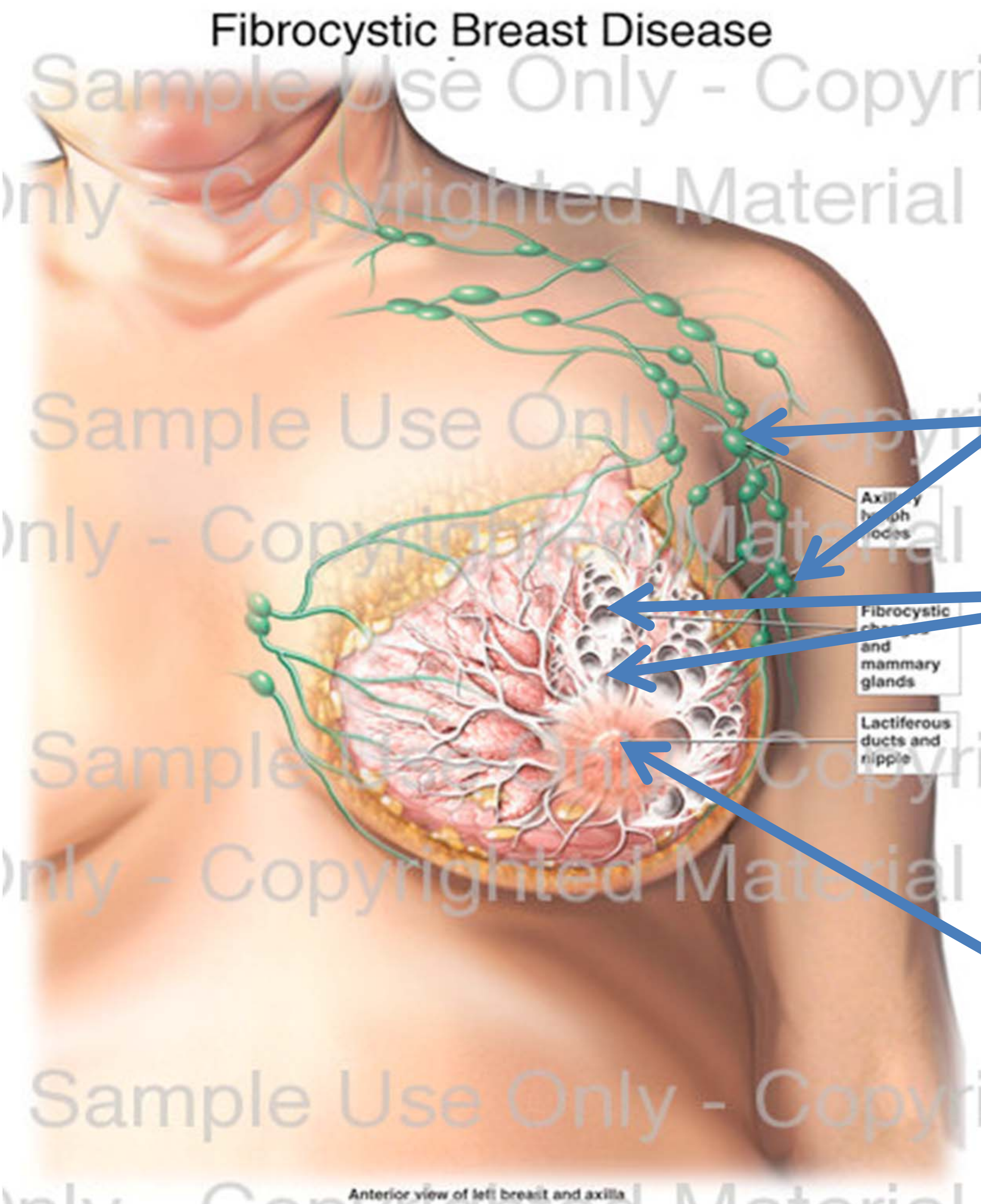
1. Chest wall
2. Pectoralis muscles
3. Lobules
4. Nipple surface
5. Areola
6. Lactiferous duct
7. Fatty tissue
8. Skin


Anatomy of the Breast
Ribs
Sternum
Muscle
Lobules
Areola
Nipple
Fat
Ducts
© MedicineNet, Inc.


Lymph
nodes
Fat


Entendiendo el cáncer de mama
¿Qué es el cáncer de mama?
Tipos de cáncer de mama
Auto-examen mamario (AEM)
Causas del cáncer de mama
Estadificación

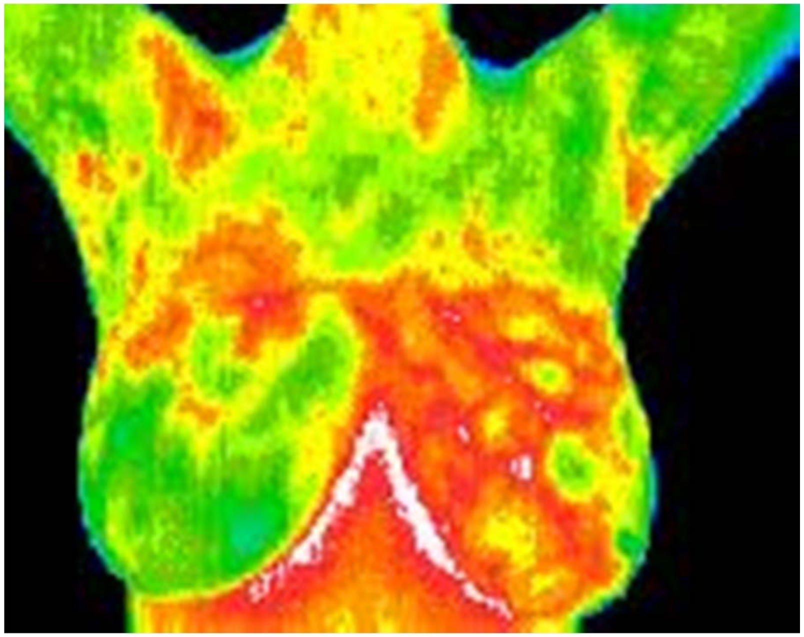
Fibrocystic Breast Disease



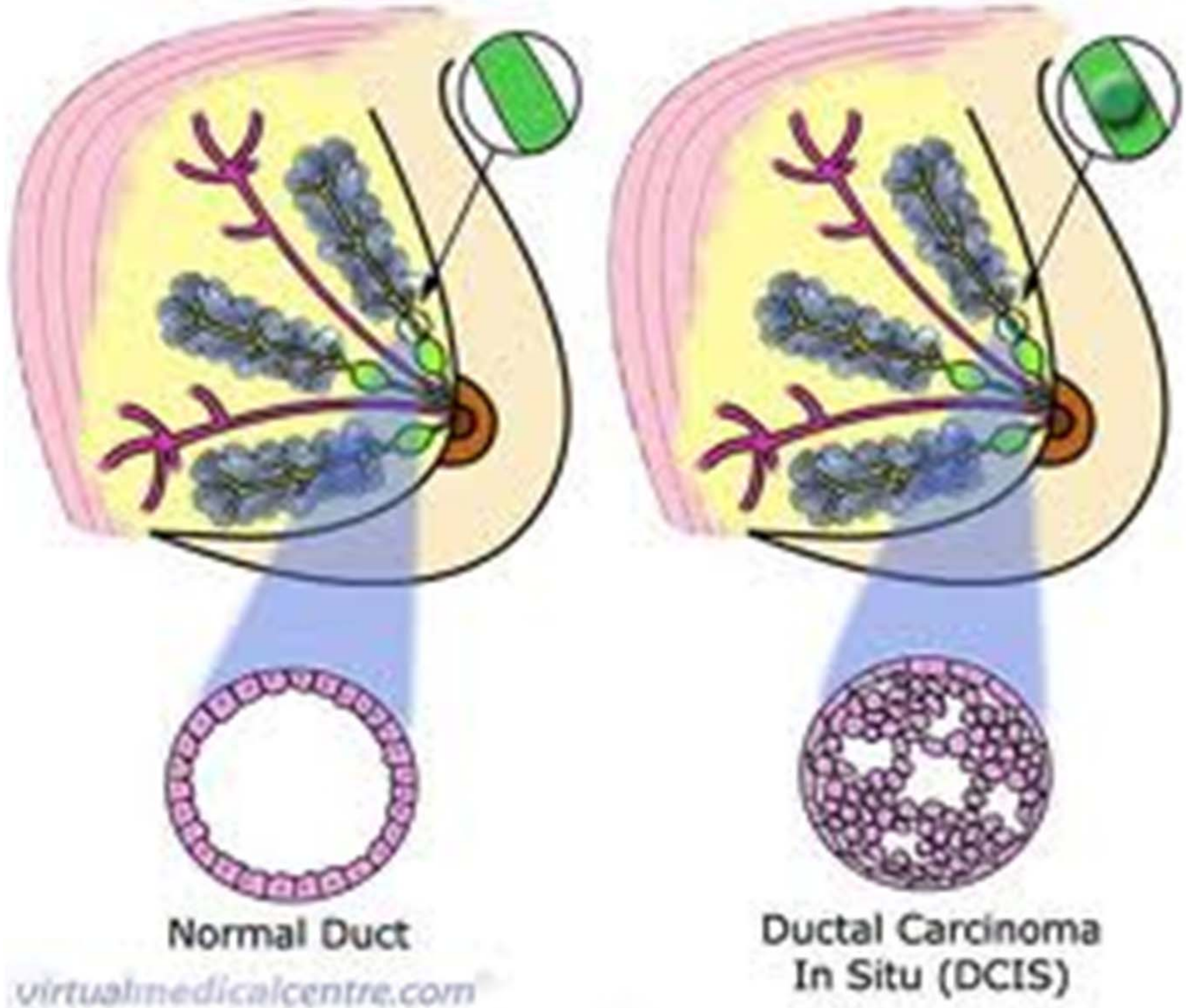
axillary lymph nodes

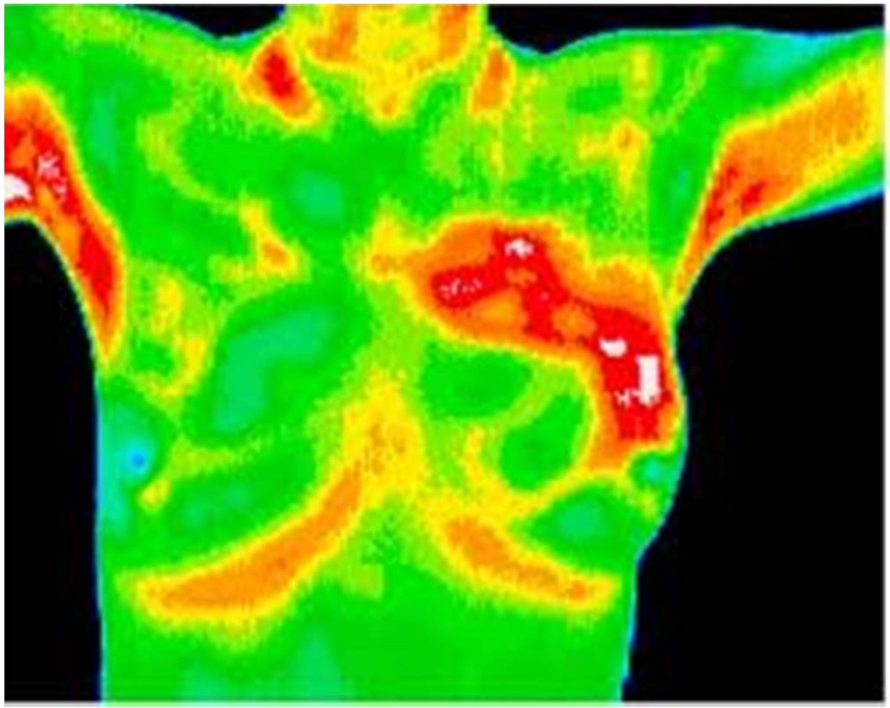
fibrocystic changes mammary glands

lactiferous ducts and nipple

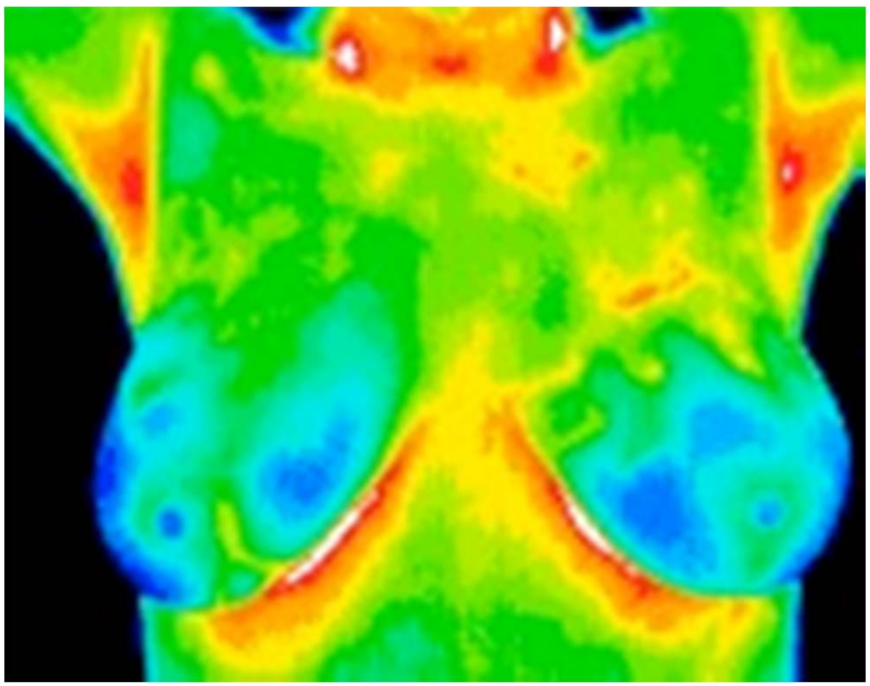


fibrocystic thermogram

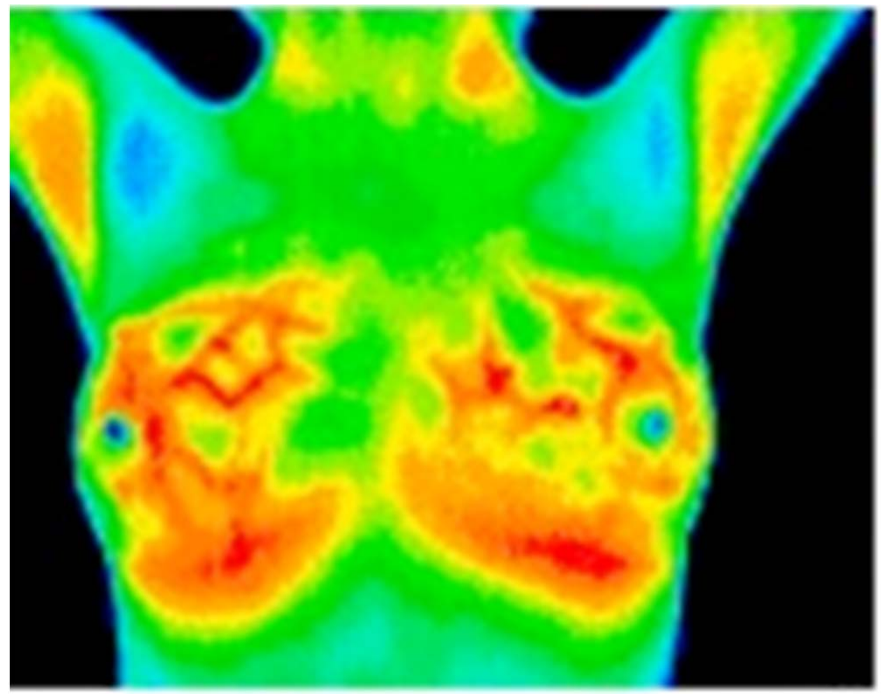

Normal Duct
virtualmedicalcentre.com
Ductal Carcinoma
In Situ (DCIS)



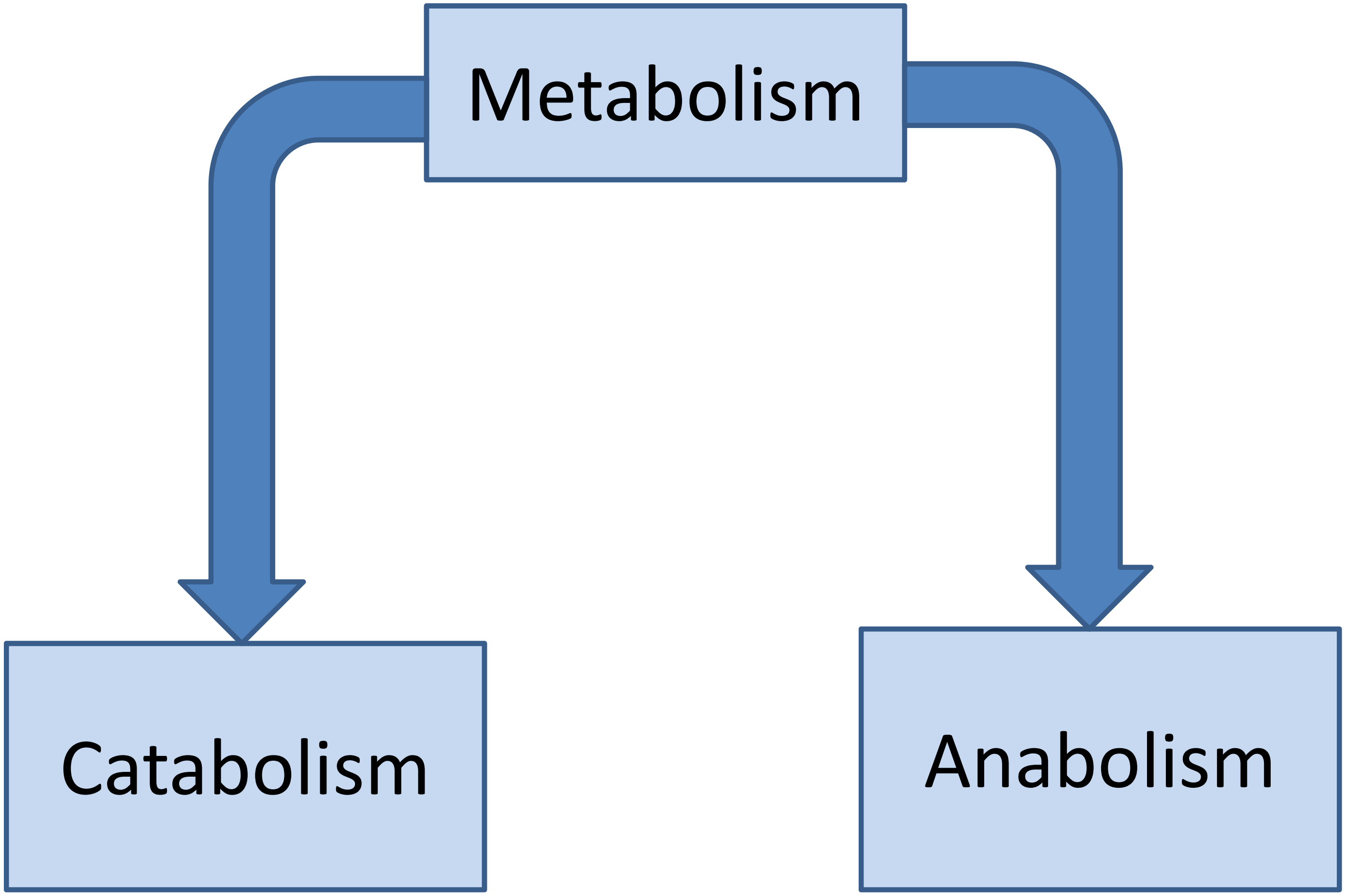
Ductal Carcinoma in Situ thermogram



normal

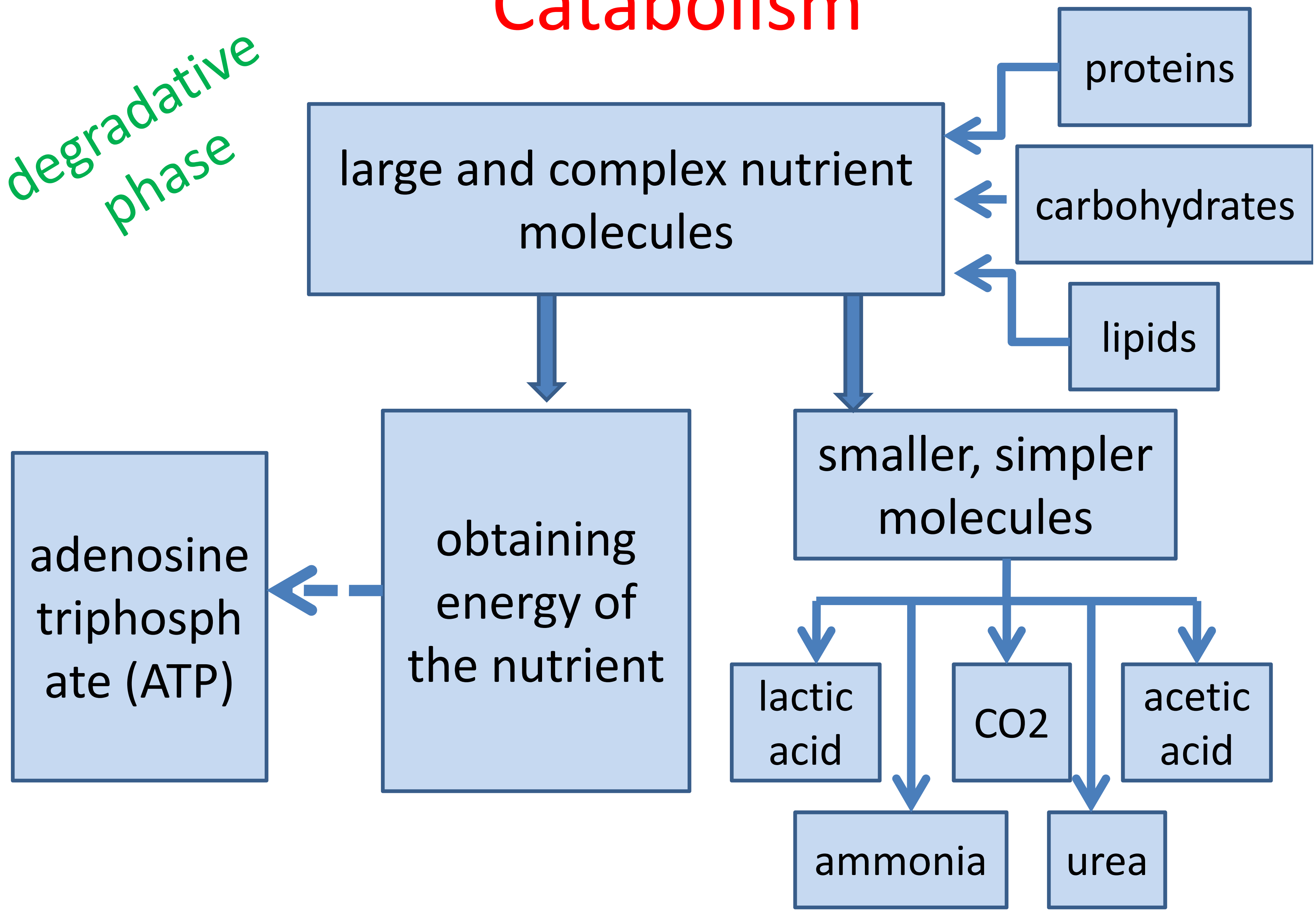


4 weeks pregnant



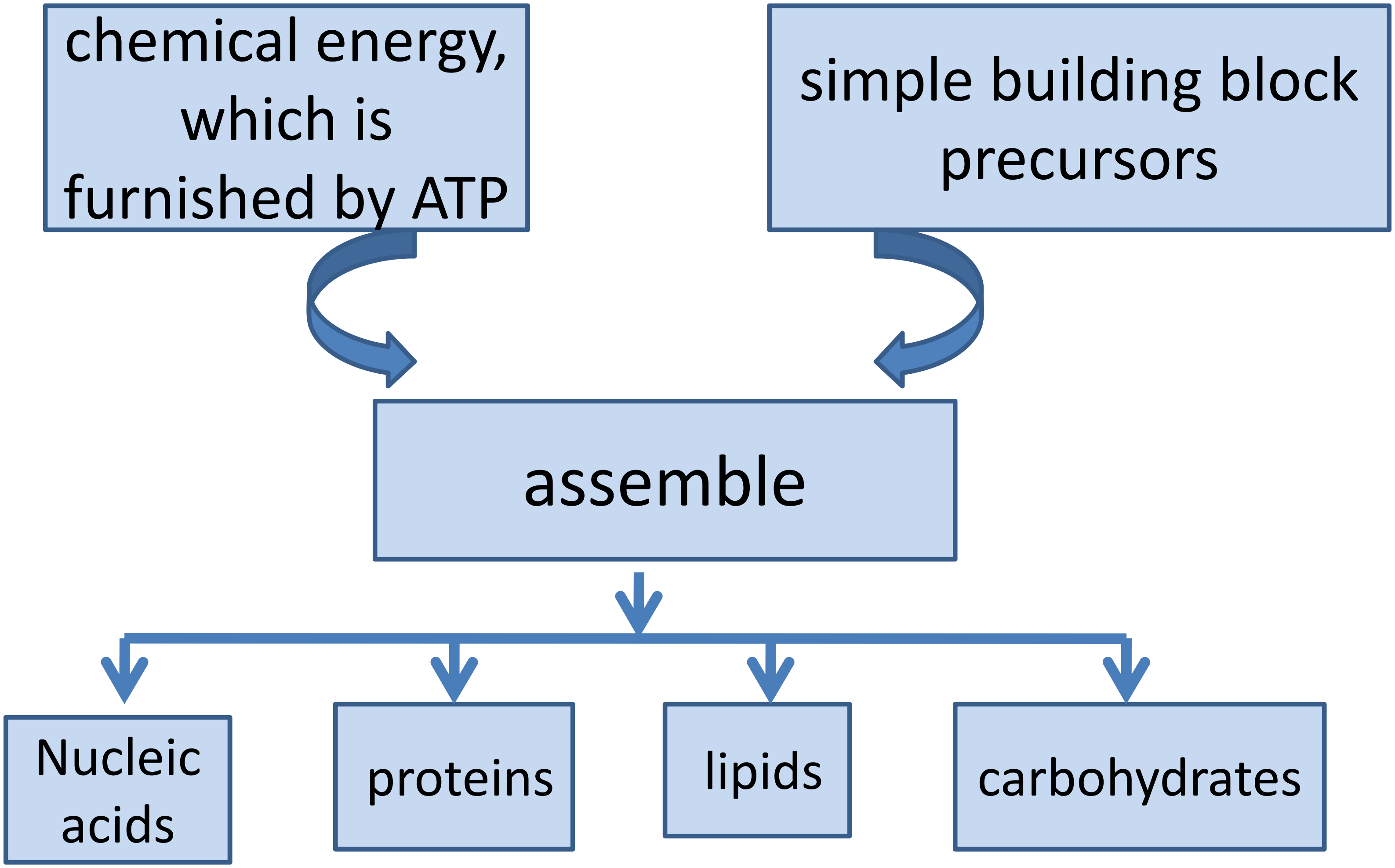
Metabolism
Catabolism
Anabolism

Catabolism


degradative phase
proteins
carbohydrates
lipids
large and complex nutrient molecules
obtaining energy of the nutrient
smaller, simpler molecules
adenosine triphosphate (ATP)
lactic acid
CO2
acetic acid
ammonia
urea

Building up phase

Anabolism



Normal cells

The energy produced → Is used by → cells for its division

a single cell → divides into → many cells and forms tissues

growth of → multicellular organs

Normal cells

In cell division → **each resultant part** → a complete relatively small cell

newly formed cells → **grow rapidly** → reaching the size of the original cell

Cancer cells

Lose

ability
to differentiate

into organs

Cancer or

dividing undifferentiated
mass of cells

Cancer cells do not obey normal pattern of tissue formation

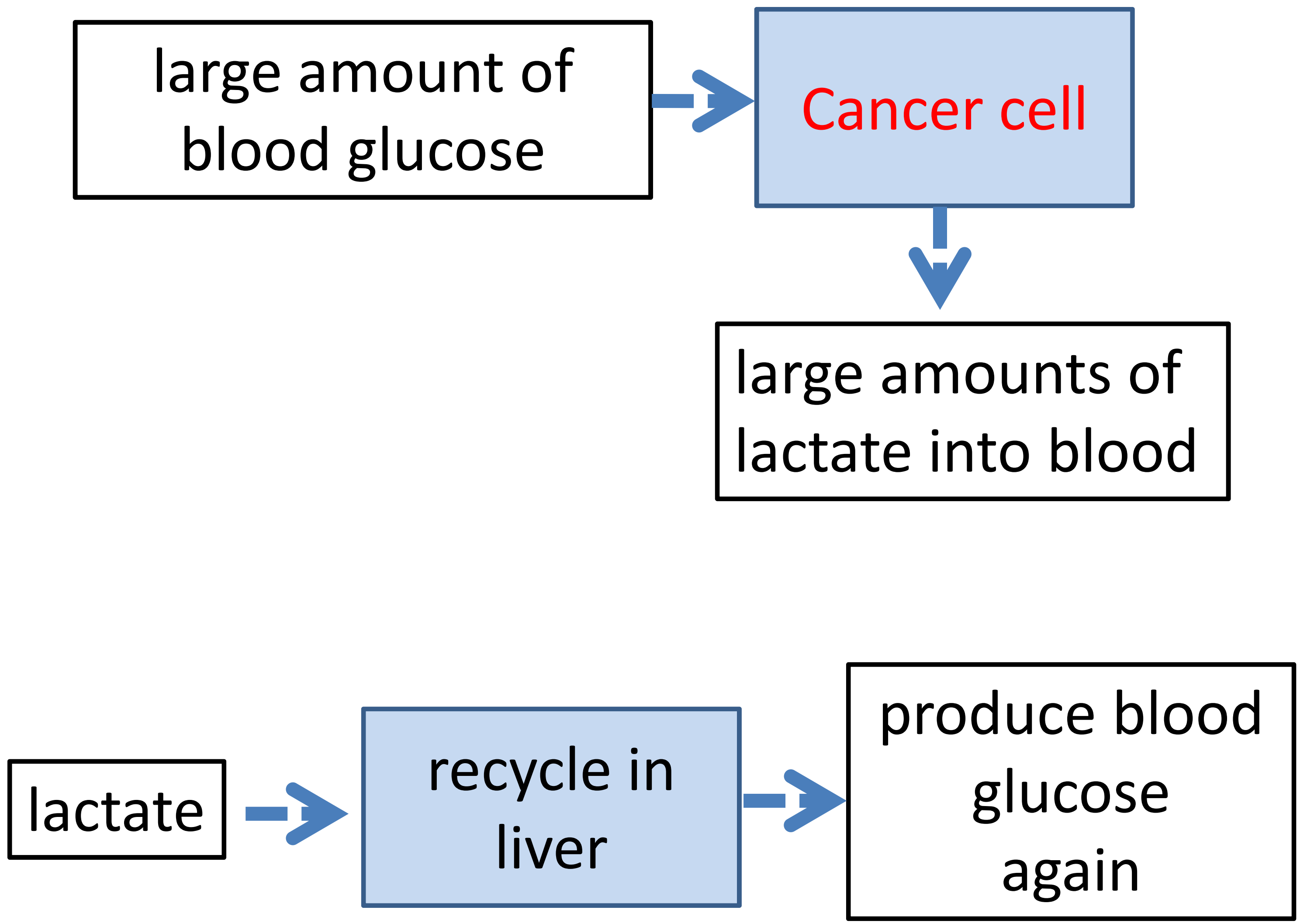
have a distinctive type of metabolism

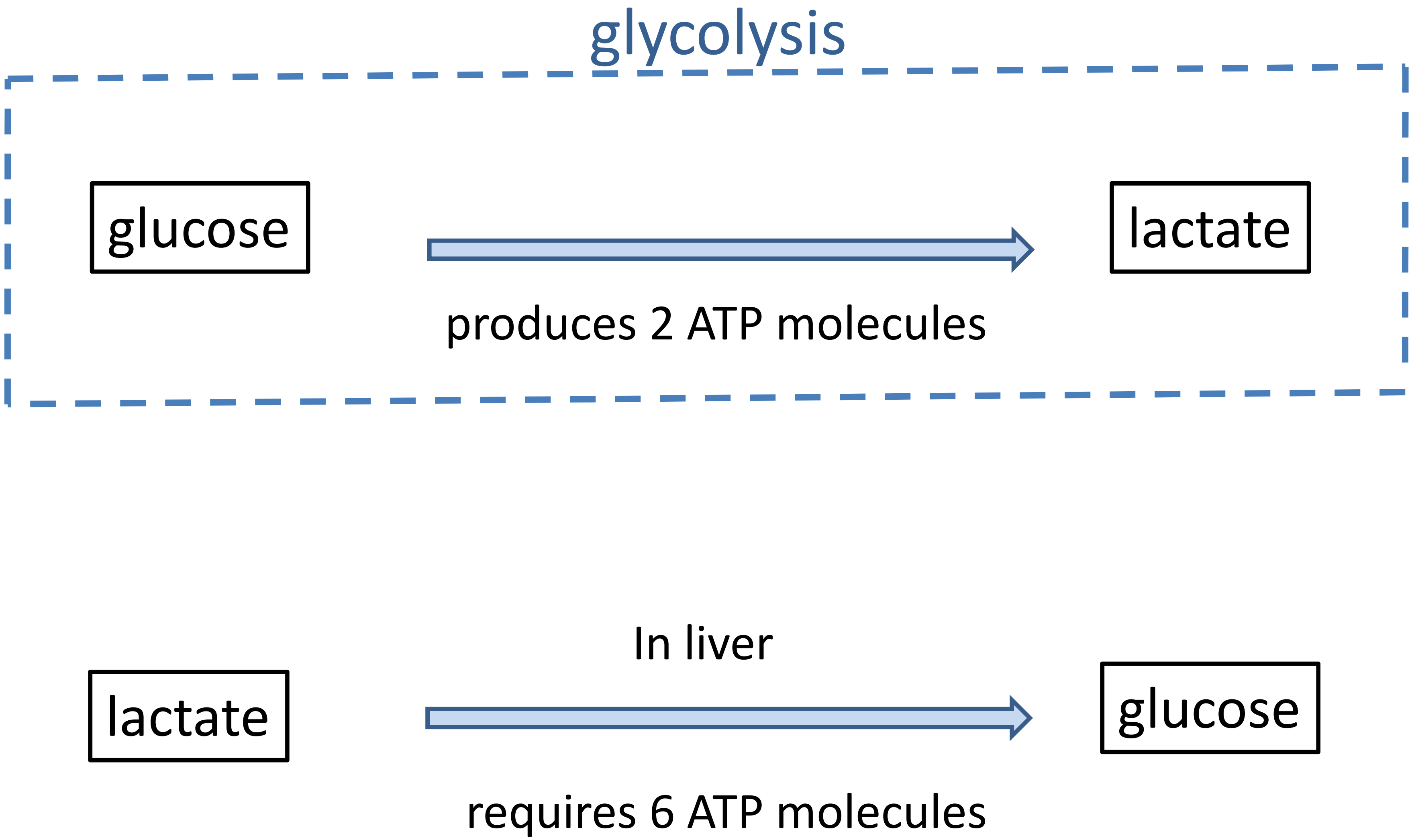
malignant cells → utilize → 5 to 10 times as much glucose

convert most of it → into → Lactate instead of pyruvate

lactate → a low energy compound

pyruvate → a high energy compound


large amount of blood glucose
Cancer cell
large amounts of lactate into blood
lactate
recycle in liver
produce blood glucose again


glycolysis
glucose
lactate
produces 2 ATP molecules
In liver
lactate
glucose
requires 6 ATP molecules

cancer cells

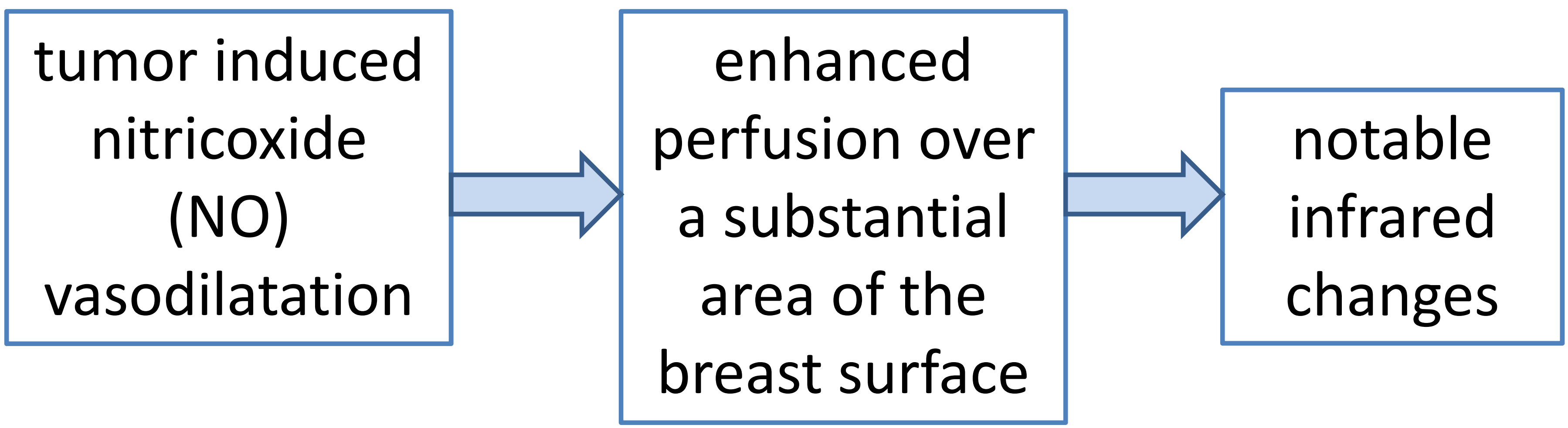
as metabolic parasites

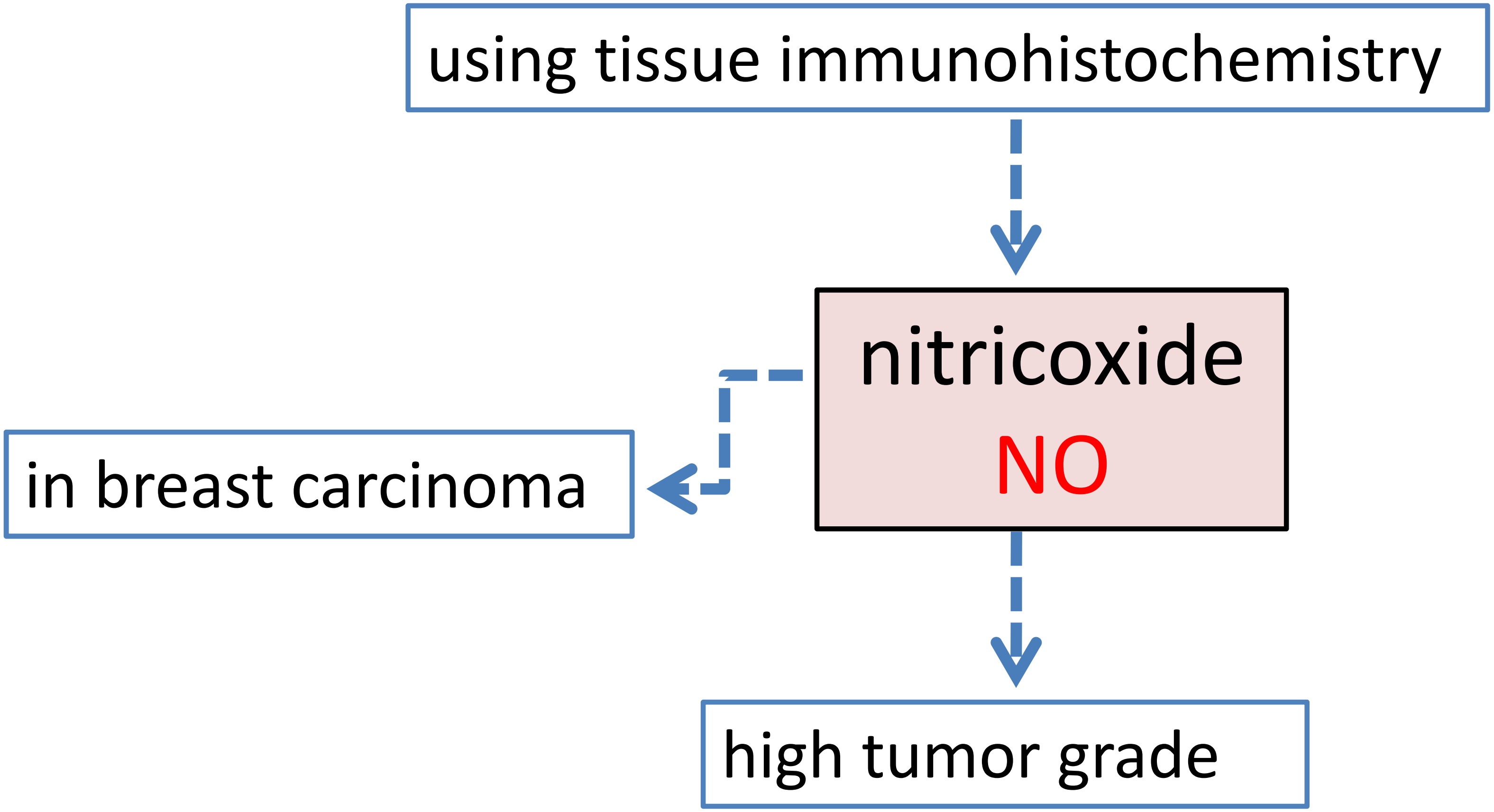
dependent on the liver

for a substantial part of their energy

High metabolic rate

Anbar


tumor induced nitricoxide (NO) vasodilatation
enhanced perfusion over a substantial area of the breast surface
notable infrared changes


using tissue immunohistochemistry
nitricoxide
NO
in breast carcinoma
high tumor grade

Cancer cell hotter than normal cell

High metabolic rate

Vasodilatation

Angiogenesis

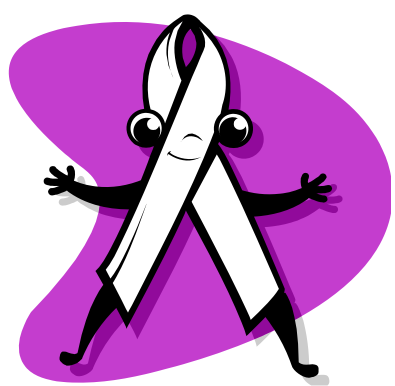
thermal IR imaging as a viable technique to visualize the abnormality

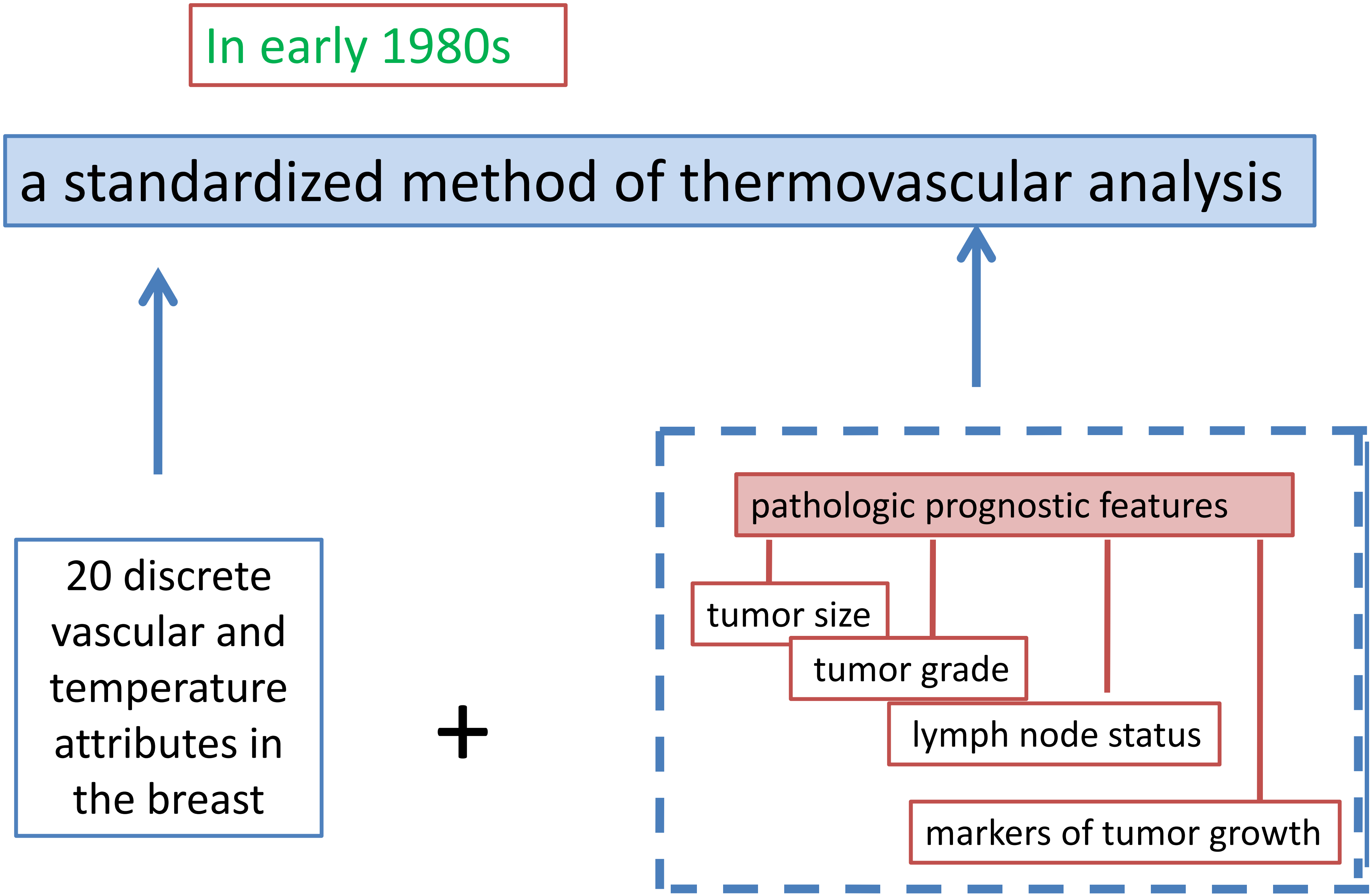
Advances in infrared (IR) camera technologies
Ultra sensitive cameras

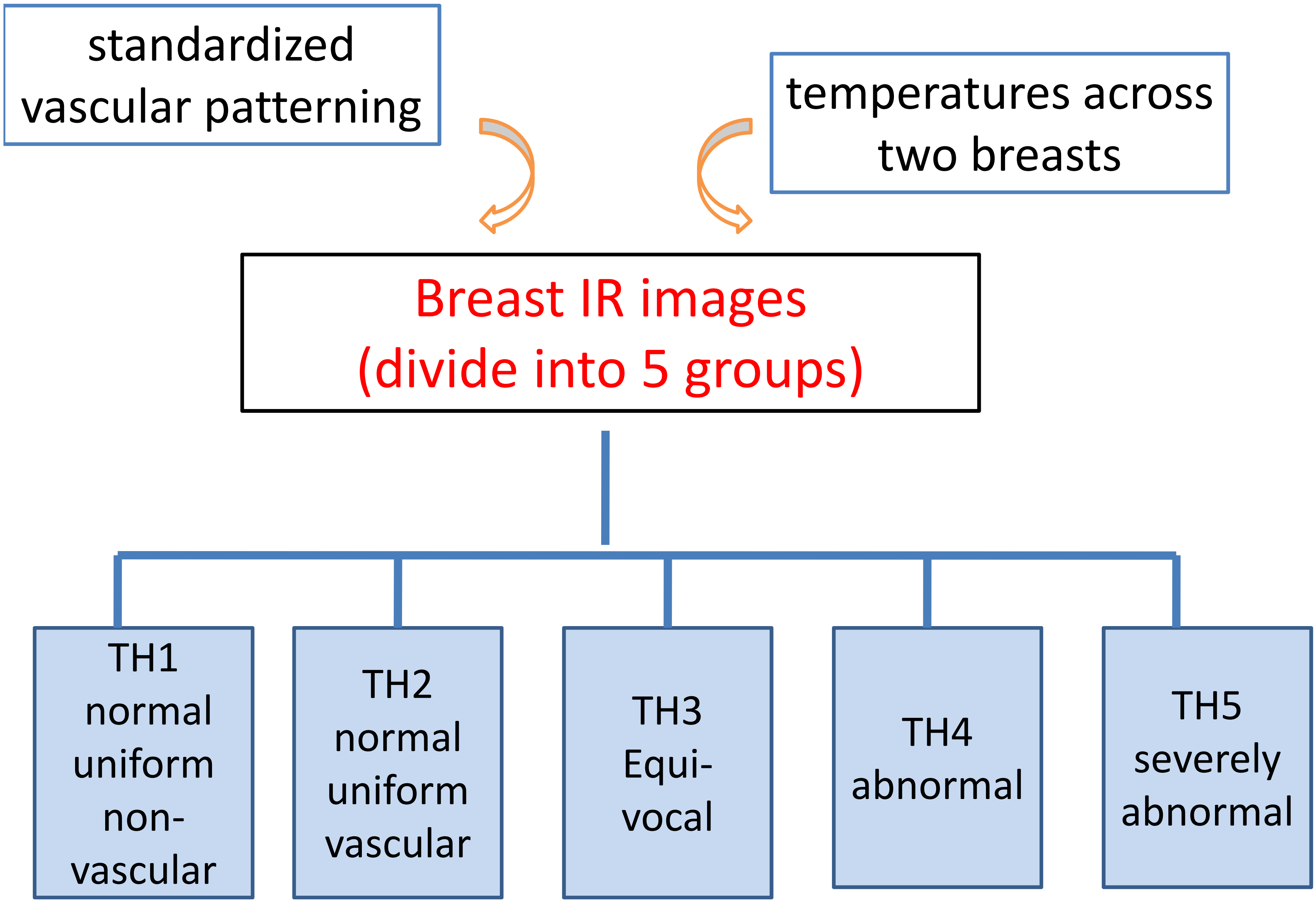
Fast computers

Advanced image processing techniques

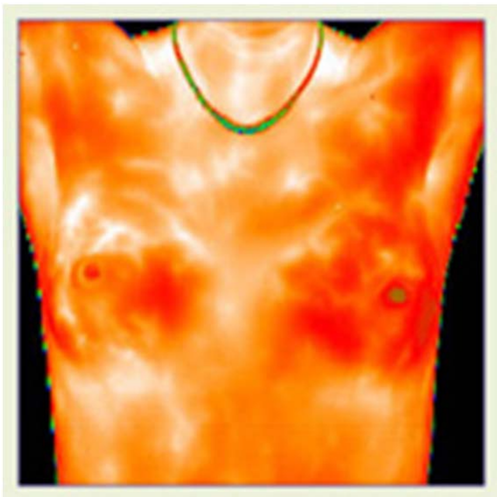
Thermography for early breast cancer detection



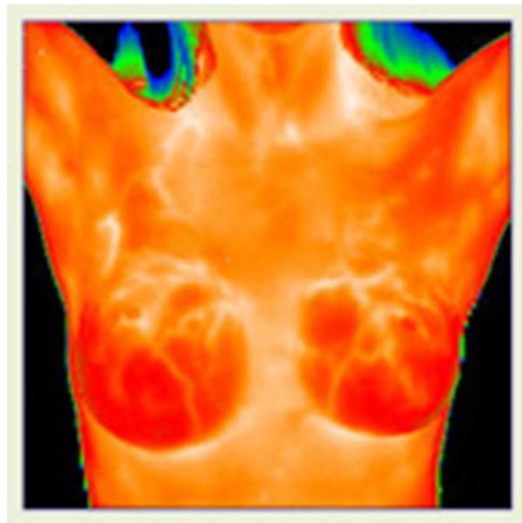

In early 1980s
a standardized method of thermovascular analysis
20 discrete vascular and temperature attributes in the breast
+
pathologic prognostic features
tumor size
tumor grade
lymph node status
markers of tumor growth


standardized vascular patterning
temperatures across two breasts
Breast IR images (divide into 5 groups)
TH1 normal uniform non-vascular
TH2 normal uniform vascular
TH3 Equi-vocal
TH4 abnormal
TH5 severely abnormal

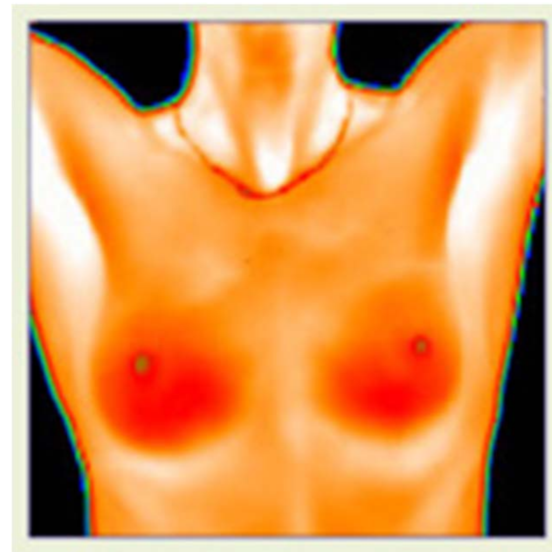
Five different categories



TH3

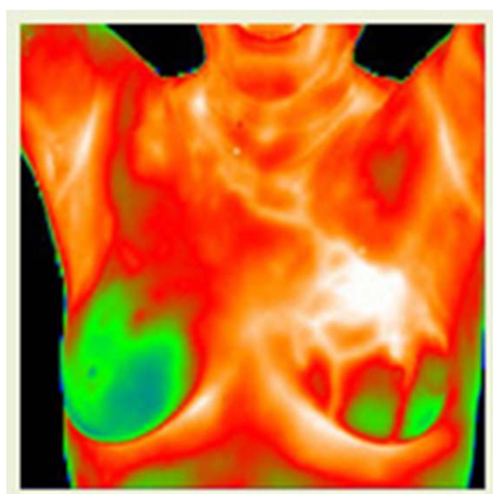


TH2

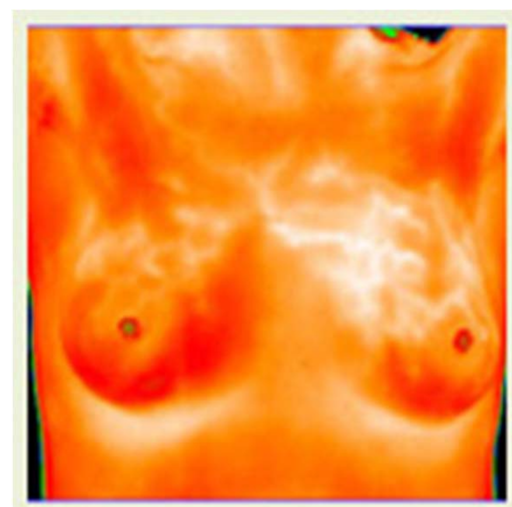


TH1

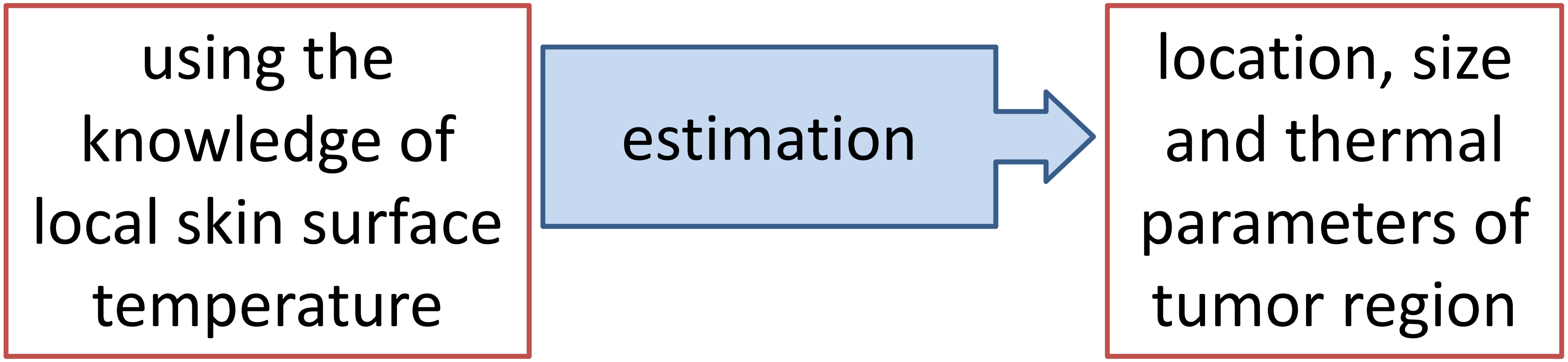
TH5



TH4



inverse problem



Pennes bio- heat equation

$$\frac{\partial T}{\partial t} = \nabla . (k \nabla T) - C_b W_b (T - T_a) + q_m$$

study of heat transfer in biological systems

- *K* the heat transfer by conduction through the tissue,
- *Qm* the volumetric blood perfusion rate whose magnitude was considered to be proportional to the arterial-venous temperature difference.
- T_a temperature of arterial blood is approximated to the core temperature of the body and the venous blood approximated to the local tissue temperature
- *T* temperature of tissue

Numerical modelling of a female breast

(Ng and Sudharsan)

- The steady state Pennes bio-heat eq.

$$K\nabla^2 T - C_b W_b (T - T_a) + q_m = 0$$

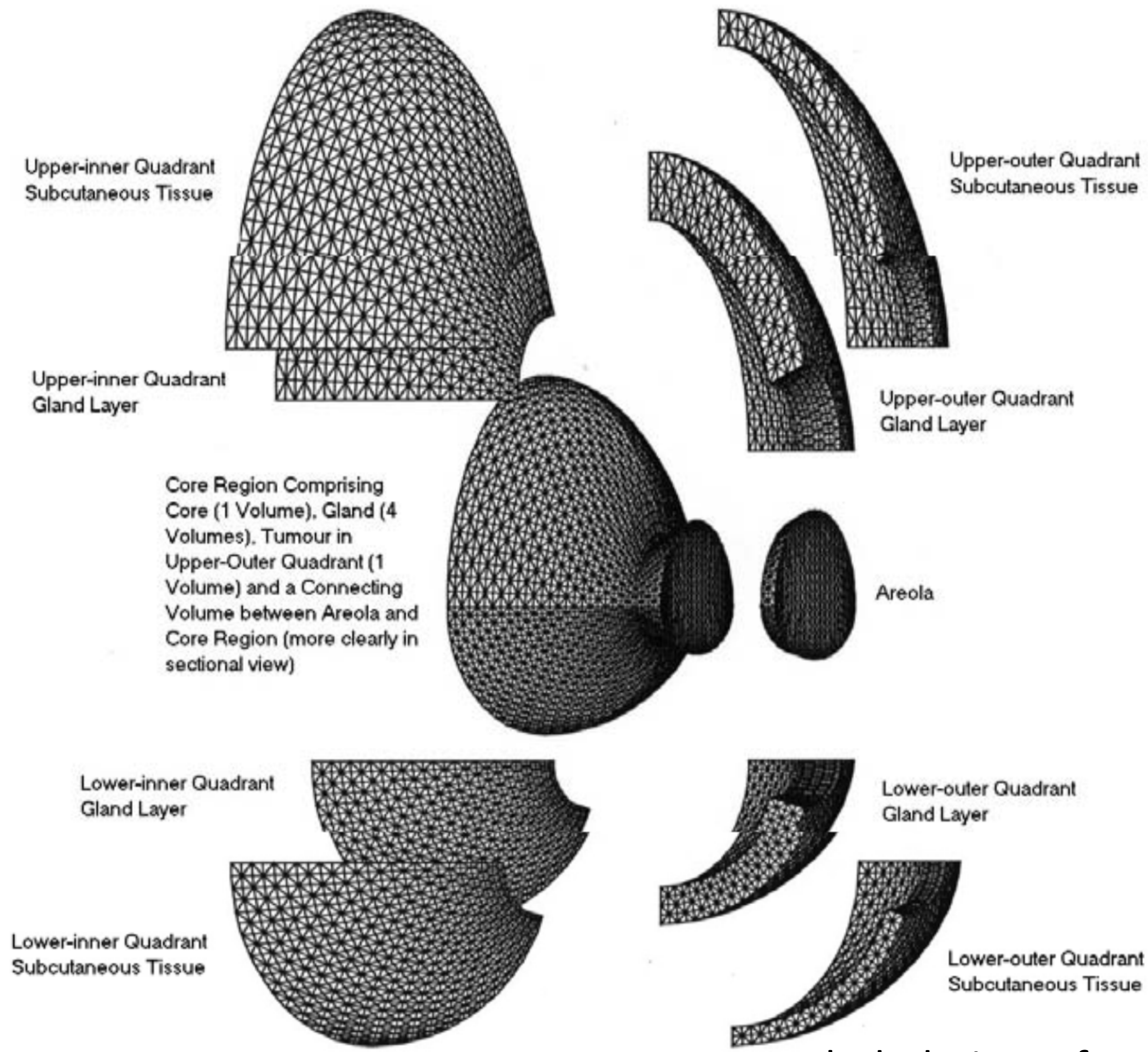
- the boundary condition $-K\nabla T = h(T - T_e)$
- *h* is the overall heat transfer coefficient due to the combined effect of convection, radiation and evaporation.
- The bottom surface of the breast is the thoracic wall with core temperature of the body
- condition in this region is $T = T_a$

Numerical modelling of a female breast

(Ng and Sudharsan)

- The breast
- divided into four quadrants
- upper-outer quadrant (armpit), upper-inner quadrant
- lower-inner quadrant , lower-outer quadrant
- With various layers
- subcutaneous fat layer
- gland layer
- muscle layer
- unequal thickness
- using finite elements

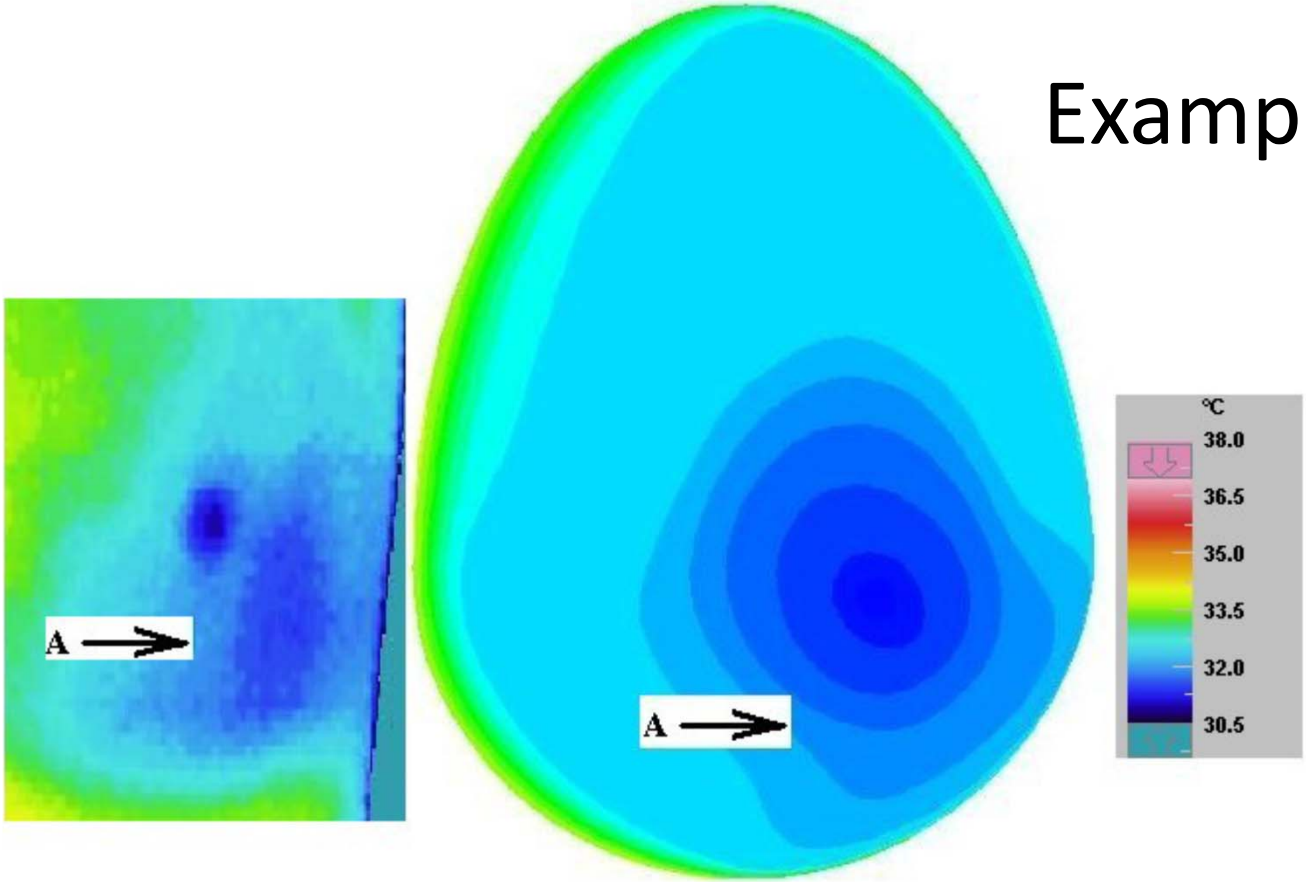
Sudharsan و Ng



Exploded View of Various Tissue Volumes

E. Ng , N. M. Sudharsan , "Effect of blood flow, tumour and cold stress in a female breast : a novel time-accurate computer simulation" Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine, 215(4), pp. 393-404, 2001

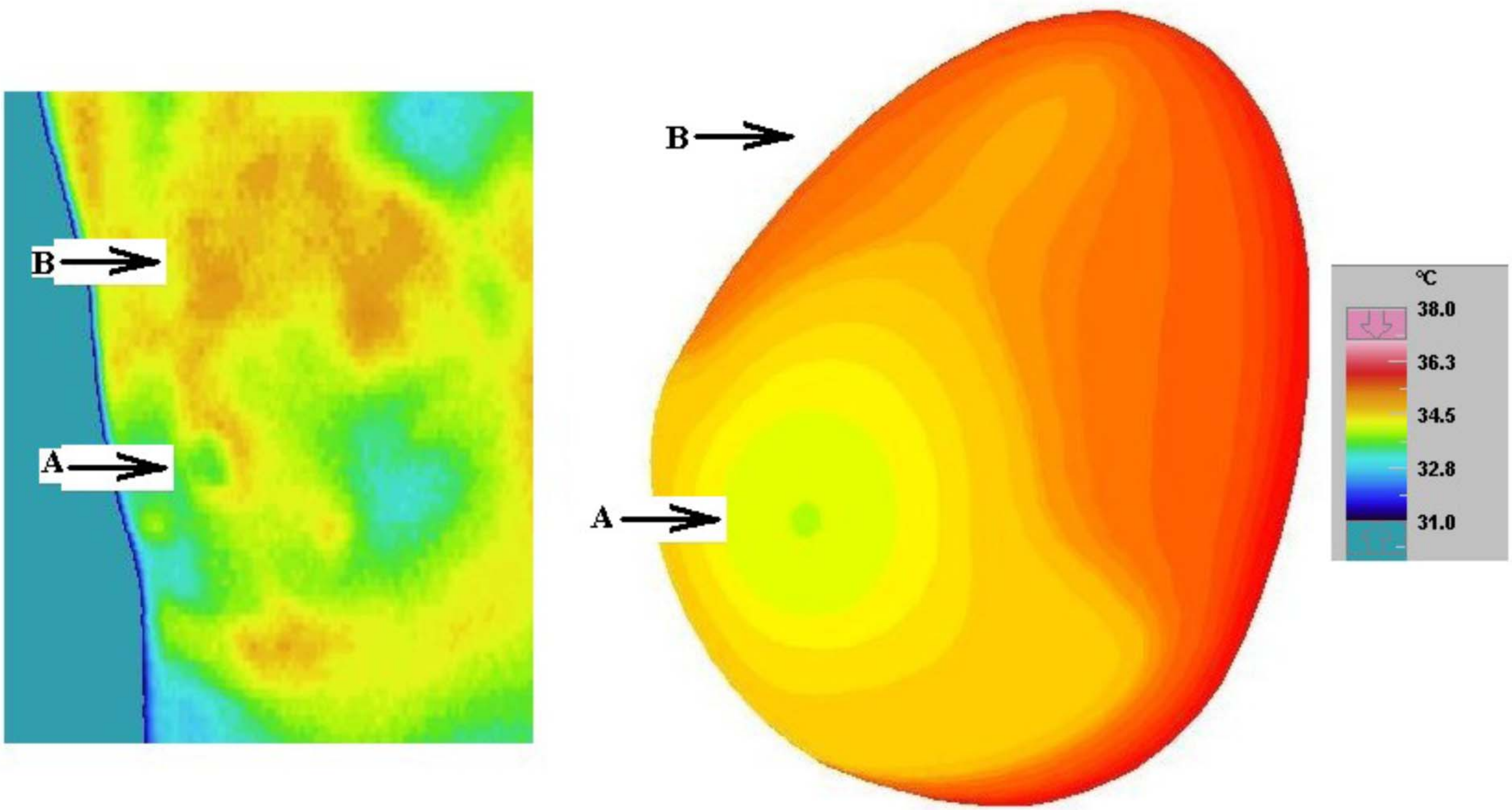
Example 1



Normal Thermogram of a Left Breast with Numerical Simulation (Volunteer 1, Age 38 years)

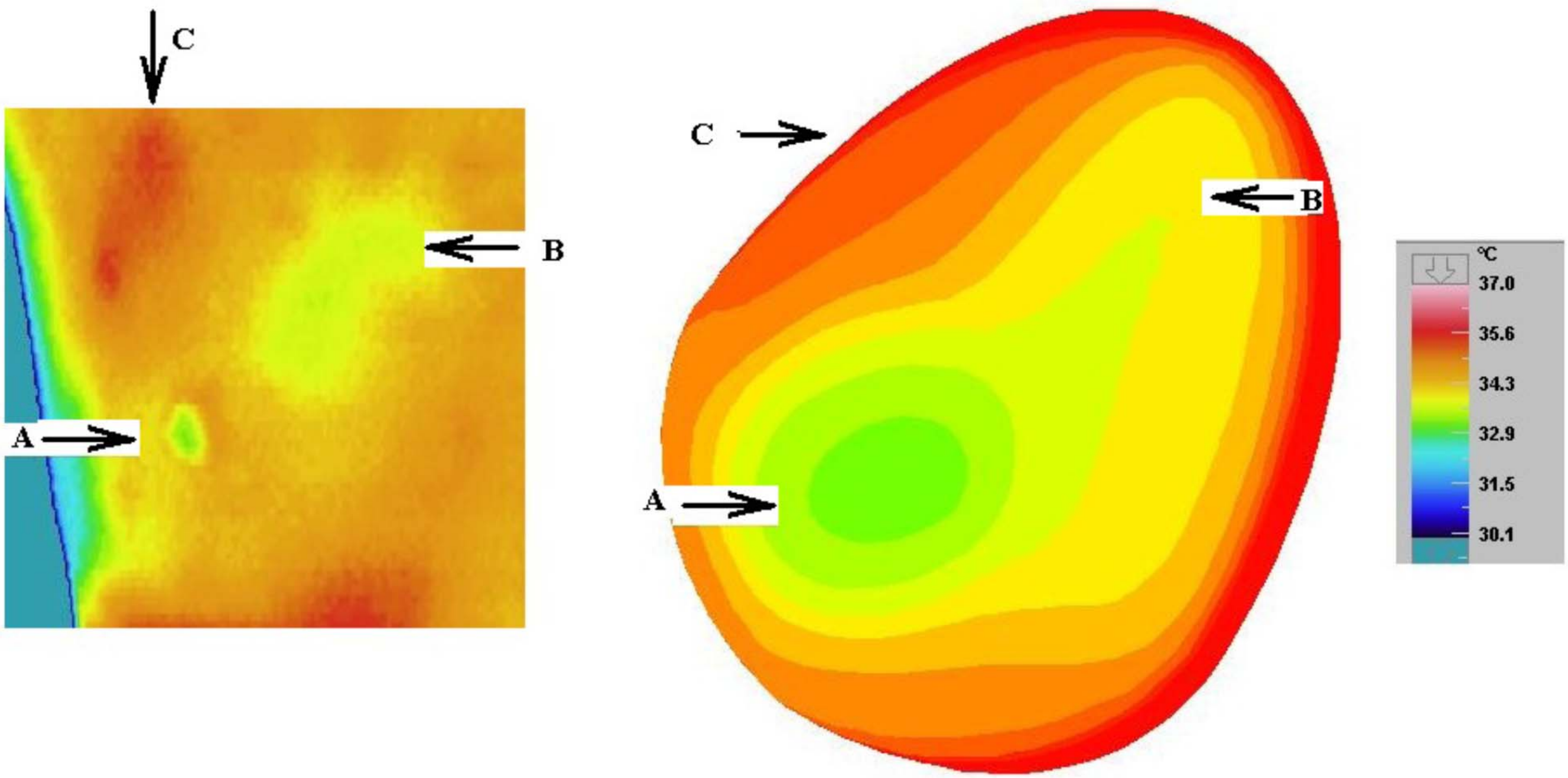
Ng , E., N M Sudharsan , Effect of blood flow, tumour and cold stress in a female breast: a novel time-accurate computer simulation Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine, 215(4), pp. 393-404, 2001

Example 2



Abnormal Thermogram of a Right Breast with Numerical Simulation (Volunteer 2, Age 47 years)

Example 3



Normal Thermogram of a Right Breast showing a cold area due to lumpectomy with Numerical Simulation (Volunteer 3, Age 43 years)

observation

numerical simulation
able to capture the presence of an abnormality

Finite element thermal analysis (Lin et al.)

A 3D finite element thermal model of breast is built

- Exploring the relationship between an embedded small tumor and the resulting surface temperature distribution.
- Choosing a tetrahedron as the basic element

Penn's bio-heat equation under steady state conditions

$$\frac{\partial}{\partial \boldsymbol{x}}(\boldsymbol{k}_x \frac{\partial \boldsymbol{T}}{\partial \boldsymbol{x}}) + \frac{\partial}{\partial \boldsymbol{y}}(\boldsymbol{k}_y \frac{\partial \boldsymbol{T}}{\partial \boldsymbol{y}}) + \frac{\partial}{\partial \boldsymbol{z}}(\boldsymbol{k}_Z \frac{\partial \boldsymbol{T}}{\partial \boldsymbol{z}}) + \boldsymbol{Q}_m + \omega_b \boldsymbol{P}_b \boldsymbol{C}_b (\boldsymbol{T}_a - \boldsymbol{T}) = 0$$

- *T* and $\boldsymbol{T}_a$ temperature of tissue and arterial blood

K_x, K_y and K_Z Thermal conductivity in *x, y* and *z* directions

$\boldsymbol{P}_b$ and C_b density and specific heat of the blood

$K_x = K_y = K_Z = K$ is assumed

$$\boldsymbol{K}\frac{\partial \boldsymbol{T}}{\partial \boldsymbol{S}}\Big|_{\boldsymbol{Surface}} = -\boldsymbol{h}(\boldsymbol{T} - \boldsymbol{T}_e)$$

h combined heat transfer coefficient due to convection, radiation and evaporation

T_e surrounding temperature

observation

- Early detection with
- a small tumor even in a deep region
- Environmental influences

Thermal simulation of breast tumors

Gonz´alez

•bioheat Pennes equation

observation

current state-of-the-art imagers are capable of
•detecting 3 cm tumors located deeper than 7 cm from the skin surface,
•tumors smaller than 0.5 cm can be detected if they are located close to the surface of the skin.

Studies

1. Qi et al. (2 models)
2. Frize et al.
3. Wiecek et al.
4. Ng et al. (2 models)

Automatic segmentation of two breasts (Qi et al.)

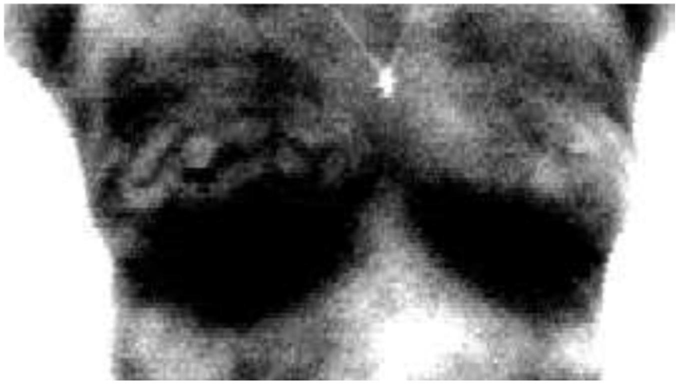
- Edge detection by canny edge detector
- Detection of 4 curves:

 left and right body boundary curves

 two lower boundaries of the breasts

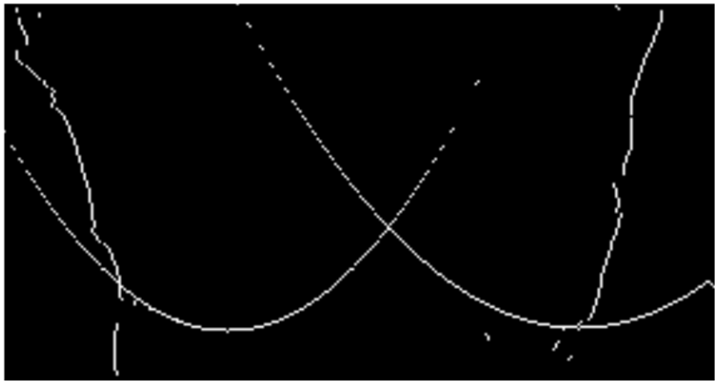
- Using Hough transform to detect the lower boundaries
- Finally segmentation of left breast from right breast

Automatic segmentation of two breasts (Qi et al.)

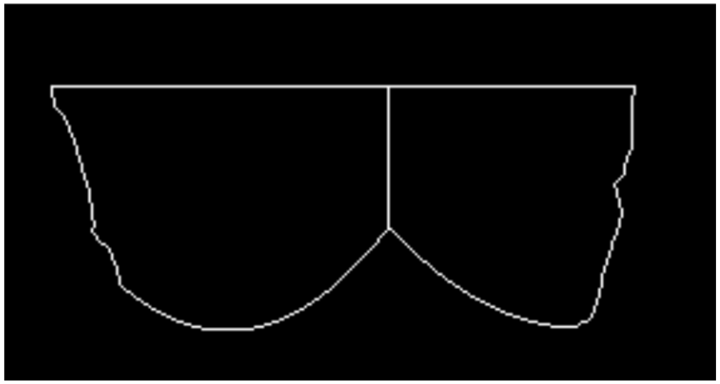


Original image

Edge detection by canny edge detector



Using Hough trans form to detect the lower boundaries



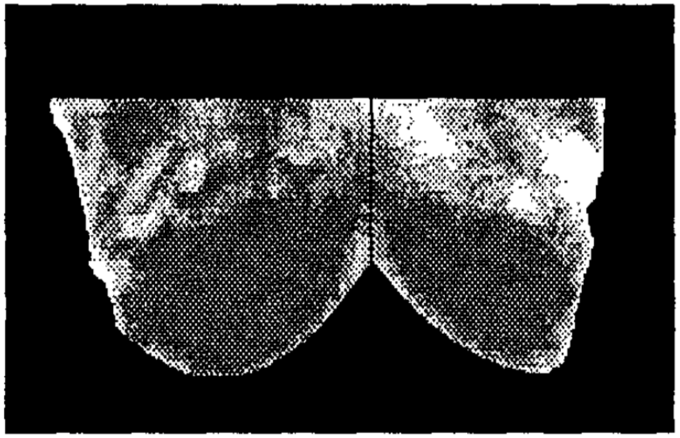
segmentation of left breast from right breast

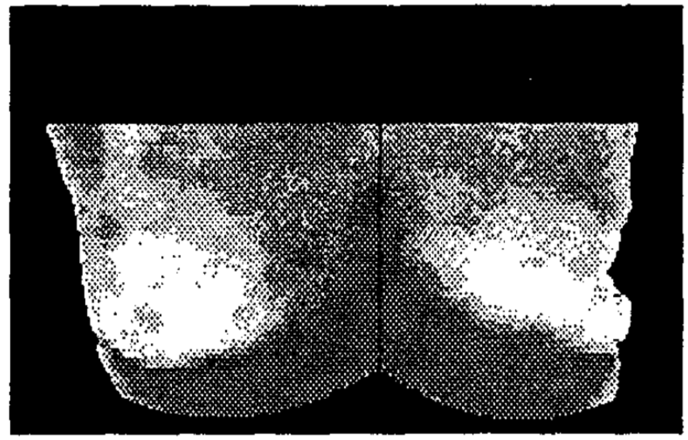
H. Qi, J. Head; "Asymmetry analysis using automatic segmentation and classification for breast cancer detection in thermograms", 2001

Feature Extraction (Qi et al.)

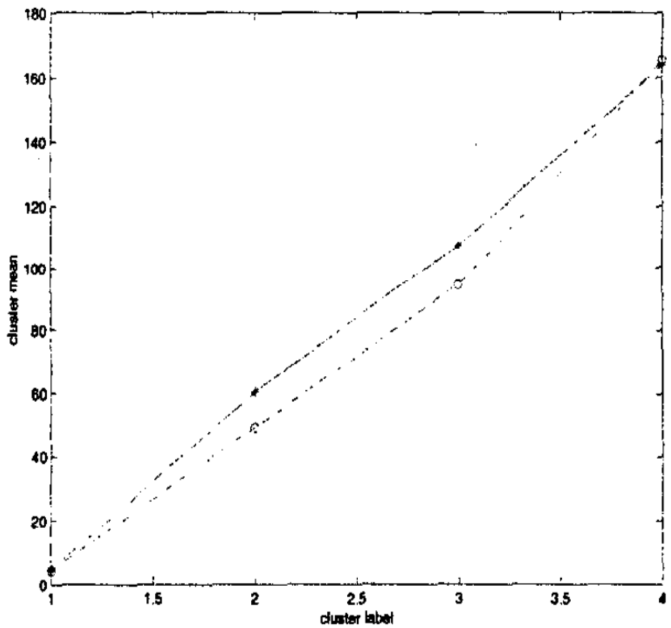
model	features	classifier
1	Means from 4 different regions and Left histogram and right histogram	K means
2	Means, variance, skewness, kurtosis, Entropy from each Breast Bilateral ratio close to1= $\left\lvert \frac{feature\ value\ from\ left\ segment}{feature\ value\ from\ right\ segment} - 1 \right\rvert$	Maximum Posterior Probability (MAP) KNN(*K-Nearest Neighbor*

Feature Extraction (Qi et al.)(model 1)

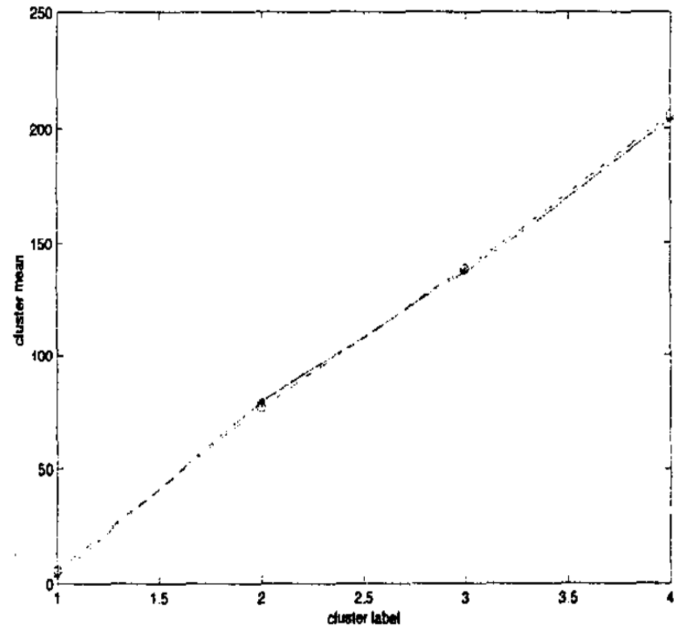




Means from 4 different regions



regions
cancer

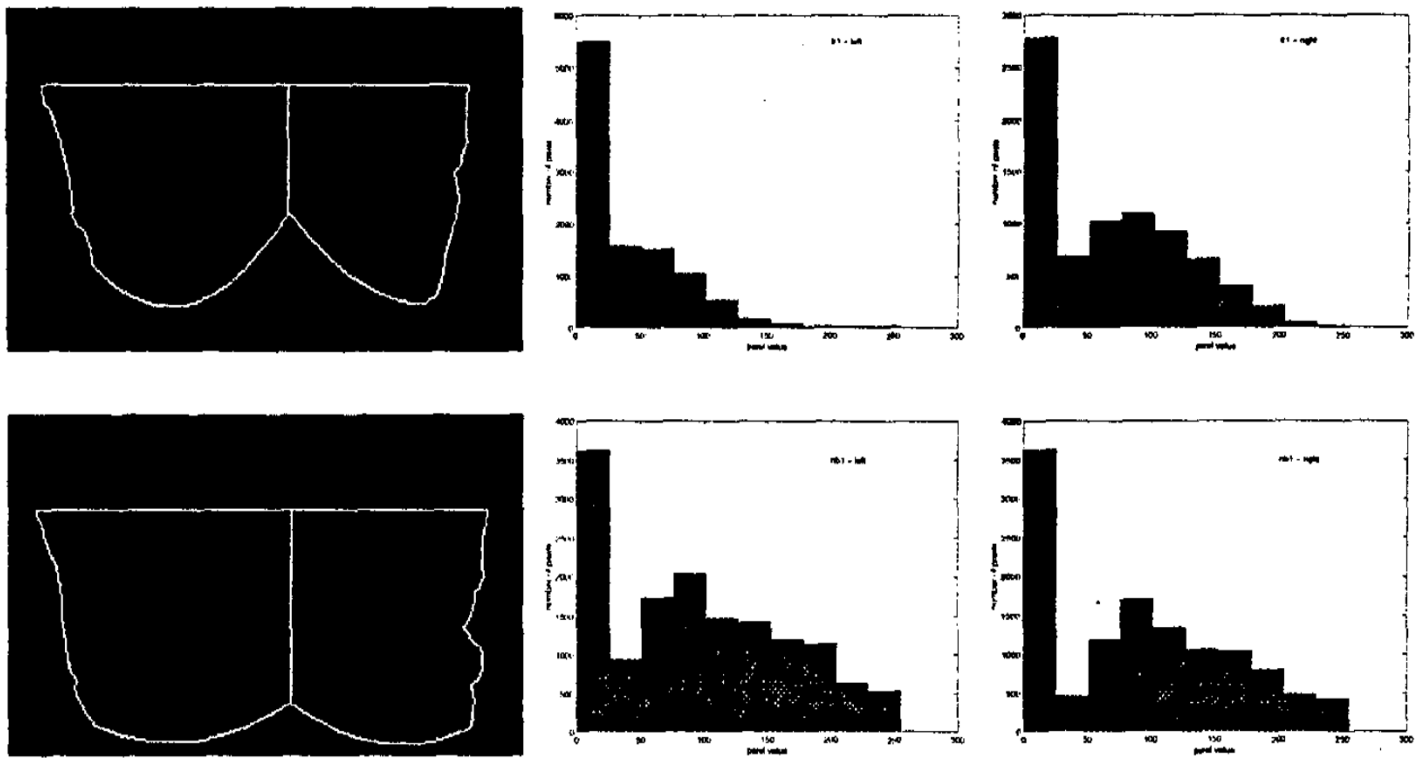


regions
Non cancer

Feature Extraction (Qi et al.)(model 1)

cancer

Non cancer

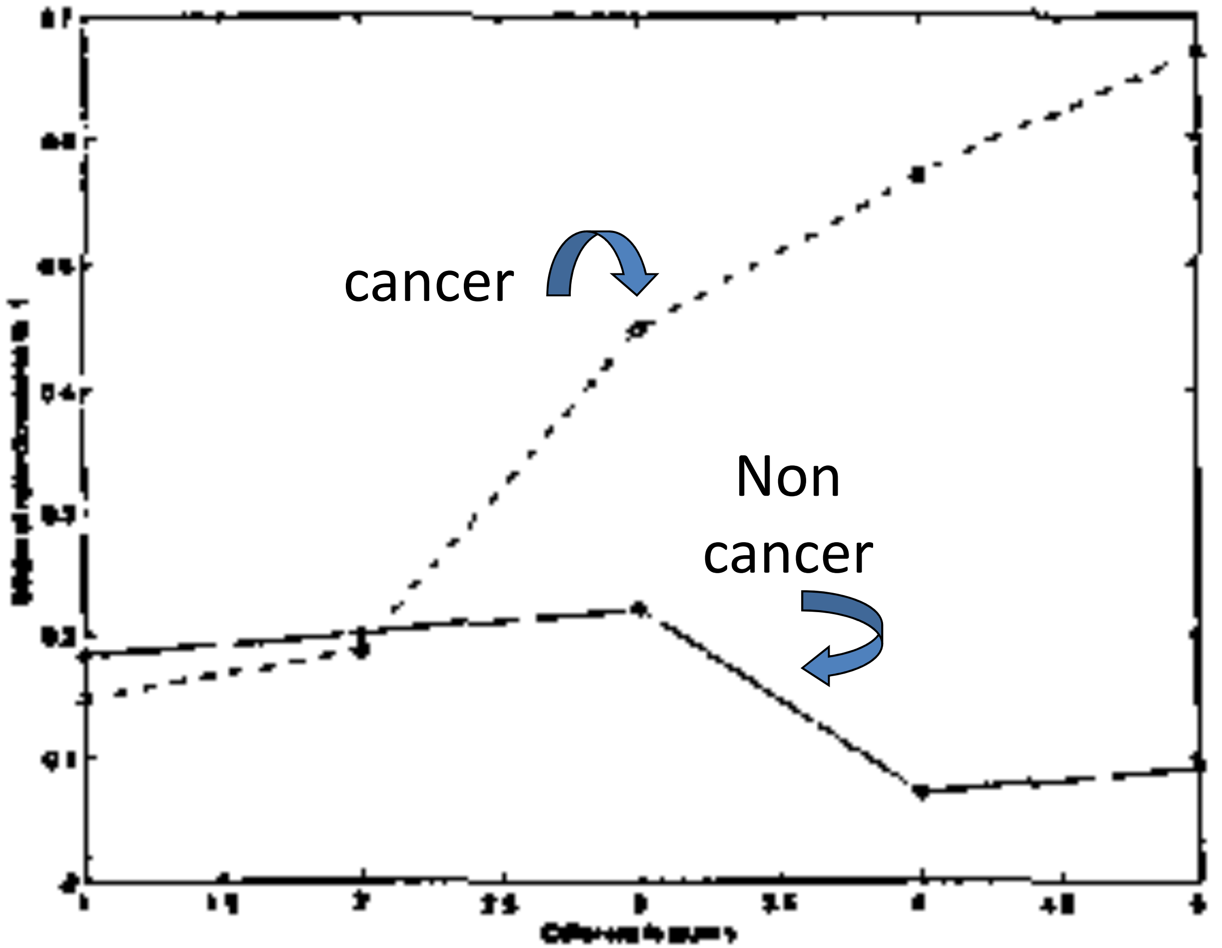


Right histogram

Left histogram

H. Qi, P. T. Kuruganti," Detecting Breast Cancer from Thermal Infrared Images by Asymmetry Analysis"

Feature Extraction (Qi et al.)(model 2)



Bilateral ratio

Means variance skewness kurtosis Entropy

Automatic segmentation of two breasts (Frize et al.)

- morphological filtering operations :enhanced by using a disk of 5-pixel radius to perform top-hat and bottom-hat
- The circular nature of each contour fitting by an ellipse
- The ellipse-fitting algorithm by Halir and Flusser's algorithm
- each breast divides to four quadrants by nipple and chin

Automatic segmentation of two breasts

(Frize et al.)

N. Scales, C. Herry, M. Frize, " Automated Image Segmentation for Breast Analysis Using Infrared Images", 2004

Frize et al.

features	classifier
for each breast and each quadrant within the breasts: mean, standard deviation, median, maximum, minimum, skewness, kurtosis, entropy, area and heat content	Neural Network back propagation

Wiecek et al.

features	classifier
First order statistical parameters (Histogram based) mean value , variance skewness, kurtosis, energy and entropy **Second order statistical parameters (co occurrence matrix based)** Energy,Variance, Difference variance,Correlation, Inverse difference, Entropy	*Artificial Neural Network* (ANN)

Feature Extraction (Ng et al.)

model	features	classifier
1	•File FH: Biodata: patient age, family history, hormone replacement therapy, age of menarche, presence of palpable lump, previous surgery/biopsy, presence of nipple discharge, breast pain, menopause at age above 50 years, and first child at age above 30 years. •File T: mean, median, modal, standard deviation and skewness of temperature for left and right breasts. •File TH: combination of FH and T. •File TD: temperature difference of mean, median, modal, standard deviation and skewness for left and right breasts. •File TDH: combination of TD and FH.	(complementary learning fuzzy neural network) FALCON-AART

Feature Extraction (Ng et al.)

model	**features**	**classifier**
2	•File FH: Bio-data from questionnaire •Temperature data from thermograms 1. Mean temperature of left breast 2. Mean temperature of right breast 3. Median temperature of left breast 4. Median temperature of right breast 5. Modal temperature of left breast 6. Modal temperature of right breast	*Artificial Neural Network* (ANN) Radial Basis Function Network (RBFN)

fractal

A fractal is a non-regular geometric shape that can be split into parts which posses self similarity. In another words, it has same degree of irregularity on all scales

a very intuitive
access to the language of fractal geometry

- consider a copy machine with an image

reduction feature

- After some ten or so cycles any initial

image would be reduced to just a point.

A fractal has several characteristic

- fractal scaling. The same level of detail occurs at all scales within the fractal so that as one delves deeper into the fractal, it never simplifies.

A fractal often has the following features:

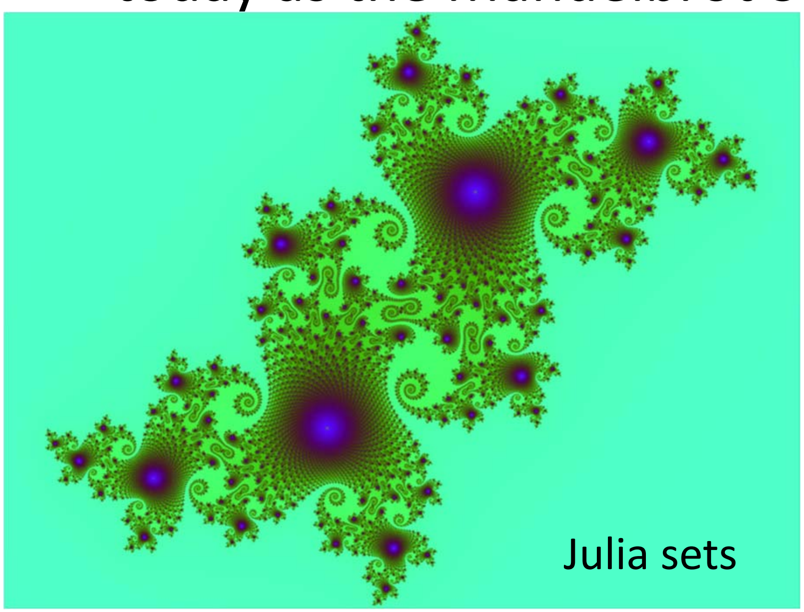
- It has a fine structure at arbitrarily small scales.
- It is too irregular to be easily described in traditional Euclidean geometric language.
- It is self similar.
- It has a Hausdorff dimension which is greater than its topological dimension.
- It has a simple and recursive definition.

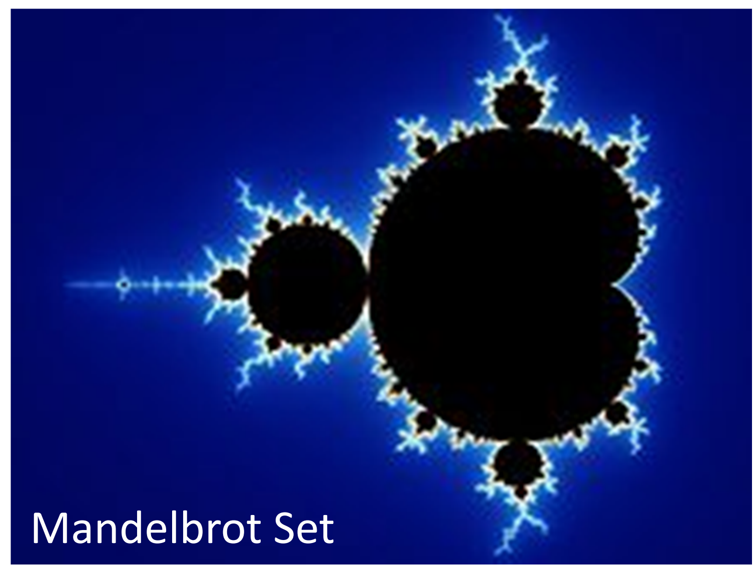
- self-similarity. The shapes seen at one scale of a fractal closely resemble the shapes seen at all other levels of detail.

No matter how many times a certain area of the fractal is magnified, self-similarity will be Maintained

•geometry between dimensions, which
means that a fractal exists in any one of an infinite number of dimensions (Brigs 20).
Imagine a string, twisted in a self-similar pattern into the shape of a square. Does the string exist as a one-dimensional line, or did it develop into a two dimensional plane?
(Brigs 65). Mandlebrot's fractal dimension for this figure is somewhere around 1.26,
neither one dimensional nor two.

The father of fractals is often considered to be a man by the name of Gaston Julia. In the early 1900’s, Julia did much research on iterated functions, and even drew some of his famous Julia sets by hand. True, there were some other works out there, such as Sierpinski’s triangle and Koch’s curve, but Julia’s work was a major breakthrough. Until the 1960’s much of the work with fractals was abandoned due to lack of technology. That changed in the 1970’s when Mandelbrot used computers to create what we now know today as the Mandelbrot Set.





Mandelbrot is largely responsible for the present interest in Fractal Geometry

- He showed how Fractals can occur in many different places in both Mathematics and elsewhere in Nature.

The most common dimensions in fractal analysis

- Hausdorff dimension
- Self similarity dimension
- Fractal dimension

Hausdorff dimension

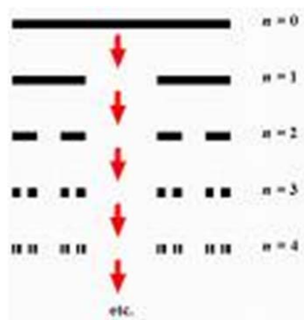
- Fractal is an object whose Hausdorff dimension is greater than its topological dimension.
- the Hausdorff dimension of a single point is zero, of a line is one, of the plane is two.
- many irregular sets(fractals) that have non integer Hausdorff dimension

Fractal Dimension(FD)

- Fractal Dimension is a statistical quantity
- indicates how completely a fractal would fill the space in different scales or magnification

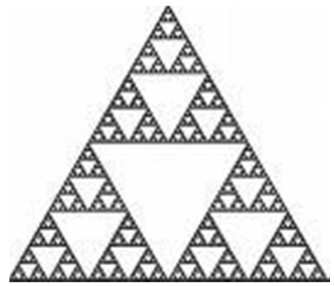
A class of examples (for generating fractals)

- Cantor set

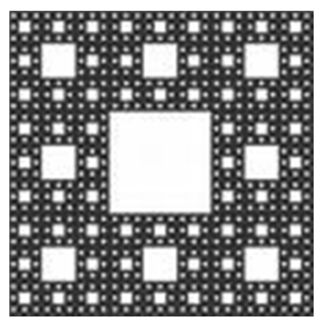


- Menger sponge

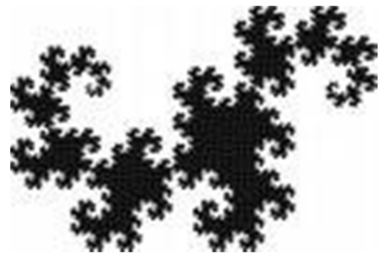
- Sierpinski triangle



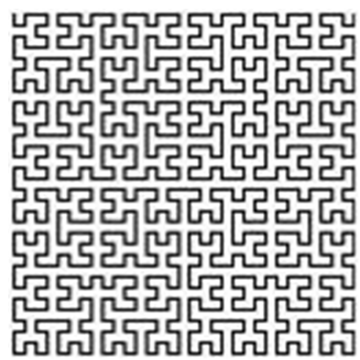
- Sierpinski carpet



- Dragon curve



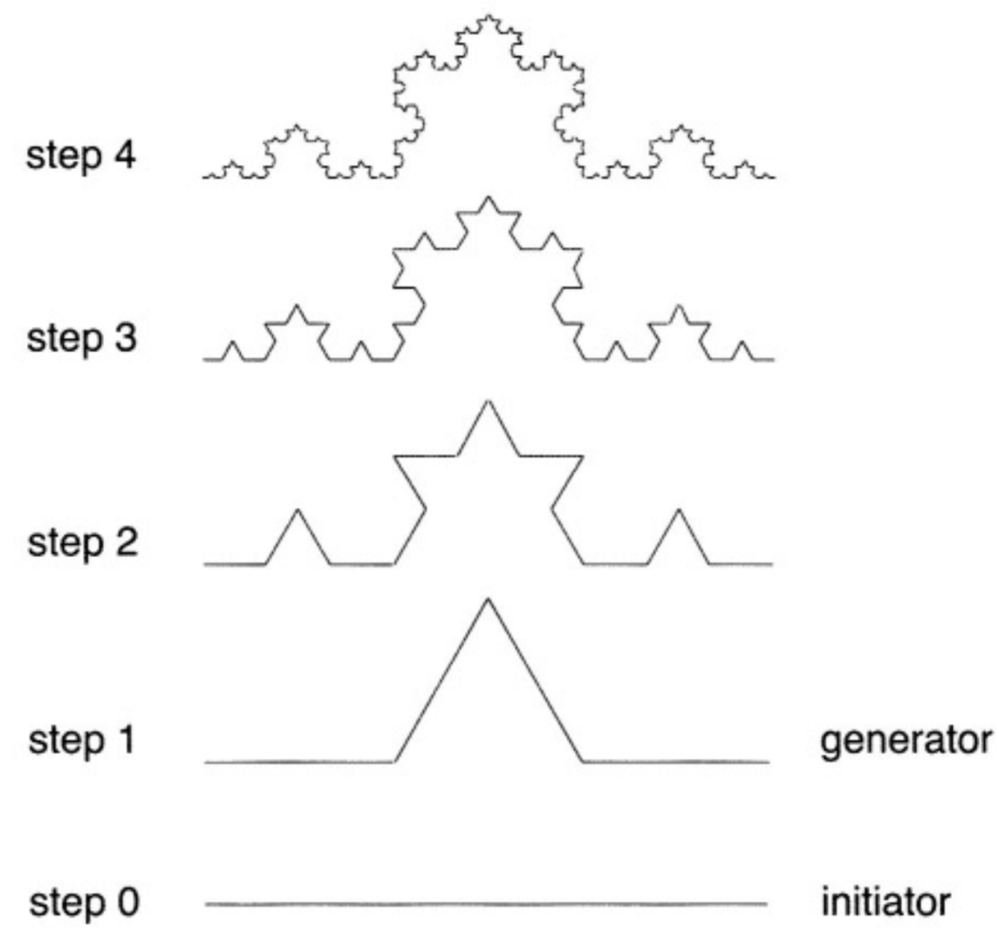
- Space filling curve



- Koch curve

Example (How to compute FD of Koch Snowflake)

- At zeroth level ($n=0$) the step size is 1
- At the next level ($n=1$), the step size is 1/3
- And so on



step 4
step 3
step 2
step 1
generator
step 0
initiator

$$N_s = 4^n, L_s = 3^{-n} \Rightarrow n = -\frac{\log L_s}{\log 3} \Rightarrow N_s = 4^{-\log L_s / \log 3} \Rightarrow \log N_s = \frac{\log 4}{\log 3} \log L_s.$$

$$\frac{\log N_s}{\log L_s} = \frac{\log 4}{\log 3}$$

FD= log 4 / log 3 which is approximately 1.26.

Example (How to create Snowflake)

- is built by starting with an equilateral triangle,
- removing the inner third of each side,
- building another equilateral triangle at the location where the side was removed,
- repeating the process indefinitely.

Examples of some fractals by their Hausdorff dimension

- Cantor set 0.6309
- Koch curve 1.2619
- Dragon curve boundary 1.5236
- Sierpinski triangle 1.585
- Sierpinski carpet 1.8928
- Menger sponge 2.7268

how to calculate fractal dimension?

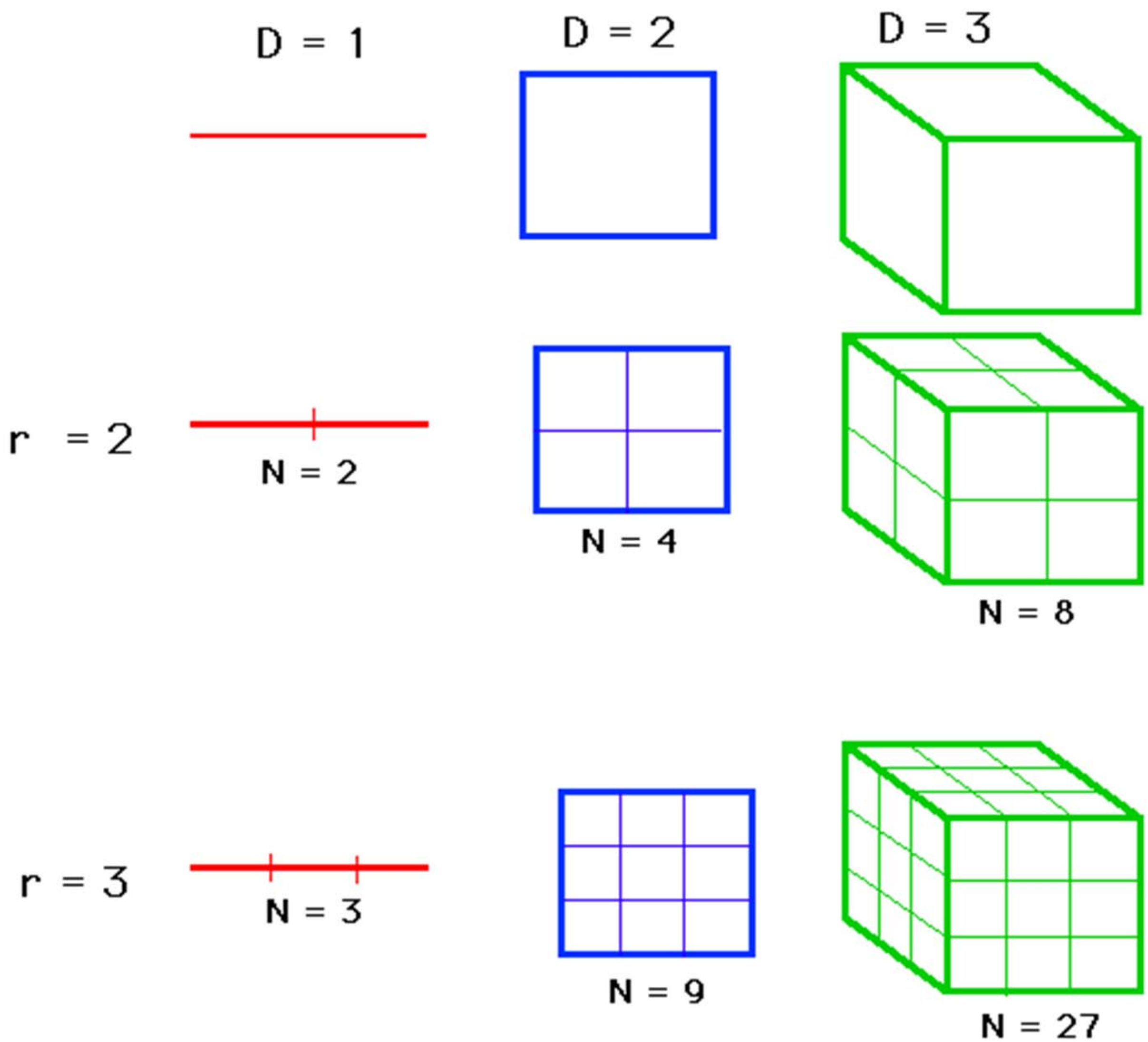
- The simplest way to calculate FD is by taking the advantage of self-similarity
- Suppose we have a one dimensional line segment. If we look at it with the magnification of two, we will see two identical line segments, and $2^1 = 2$, where 1 indicates the dimension. In a two dimensional square, with the magnification of 2, we get 4 identical shapes in both of them and $2^2 = 4$ and hence 2 indicates the fractal dimension. Finally, take a three-dimensional cube and doubling its length, breadth and height, we get eight identical cubes, that is $2^3 = 8$ and 3 indicates the fractal dimension.

This can be expressed as

$$E^D = N$$

Here, E stands for the magnification, D for dimension and N for the number of identical shapes. Applying logarithms,

$$D = \log N / \log E$$



$$N = r^D$$

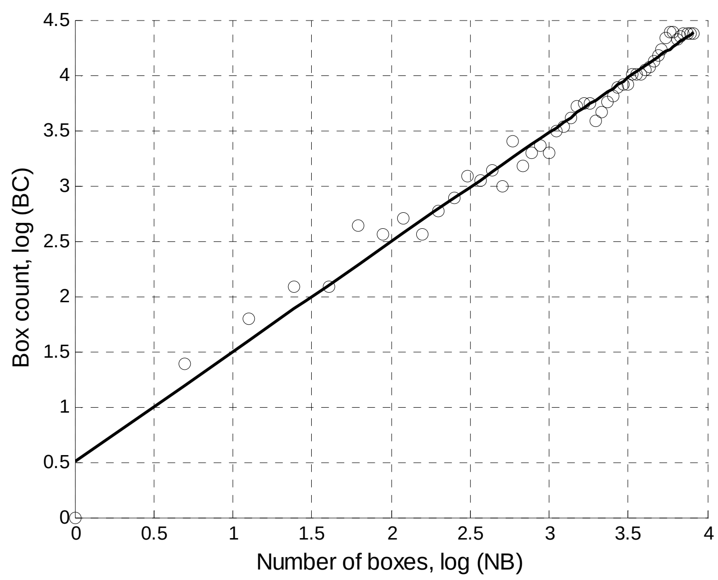
self similarity dimension

$$a \propto \frac{1}{S^D}$$

- *D* is the self similarity dimension
- *a* is the number of self similar pieces at reduction factor *(1/S),* so

$$D = \frac{\log(a)}{\log(\frac{1}{S})}$$

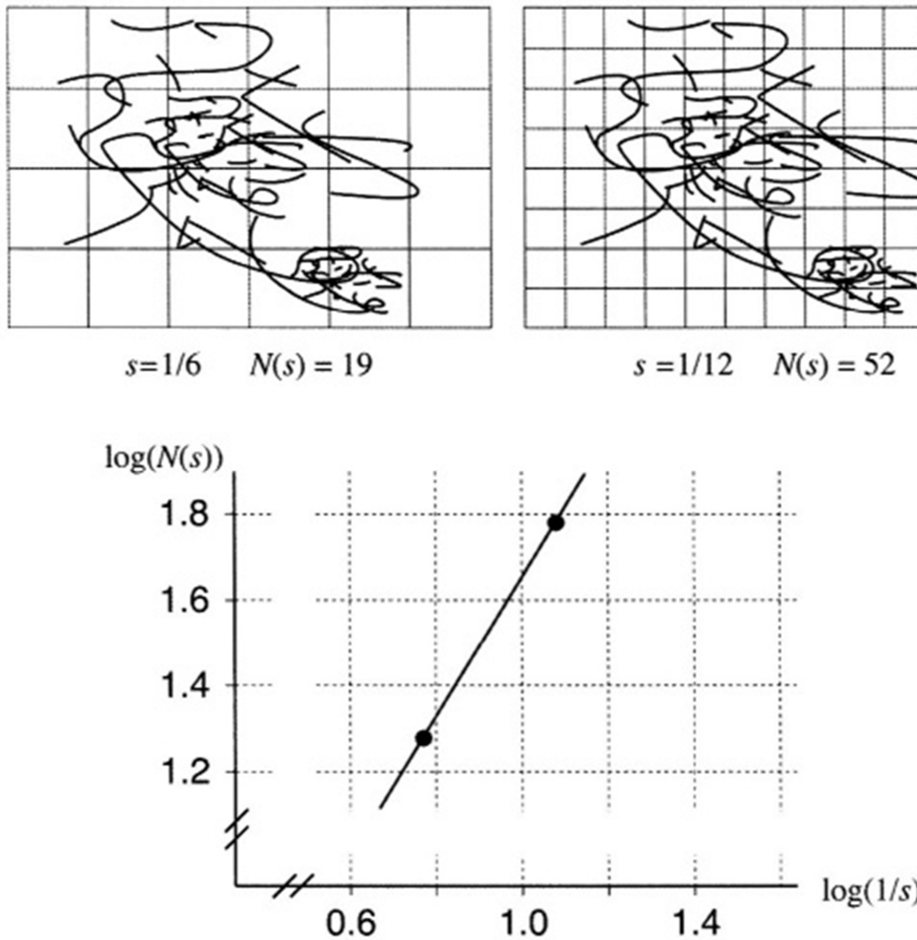
- D can be estimated by slope of the straight line approximation for a plot of log (a) vs. log(1/s).



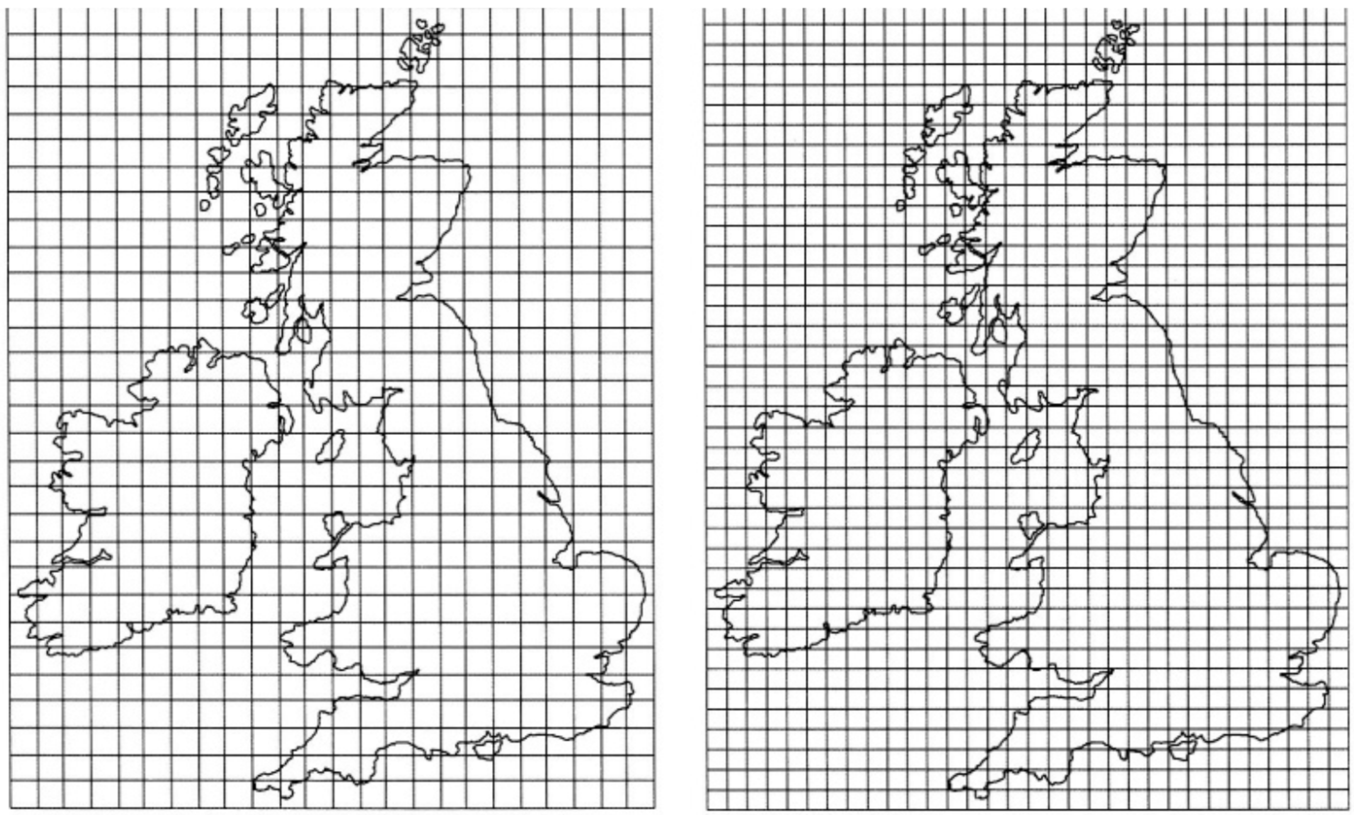
Box counting method (BCM)

- partitioning the image into square boxes with equal sizes and
- then counting the number of boxes which contain a part of the image.
- repeating the process with partitioning the images into smaller and smaller size of boxes.
- The plot of log of the number of boxes counted vs. the log of the magnification index for each stage of partitioning
- The slope of best fitting line to the aforementioned plot is the FD of pattern.

Example 1(BCM)



Example 2(BCM)
(Coastline of Britain)



$$d = \frac{\log 283 - \log 194}{\log 32 - \log 24}$$

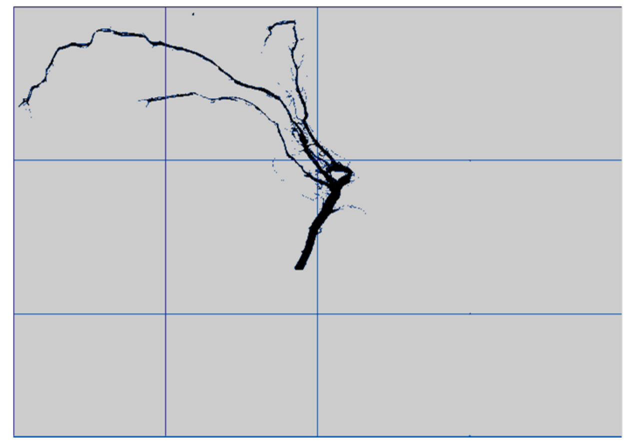
which is approximately 1.31

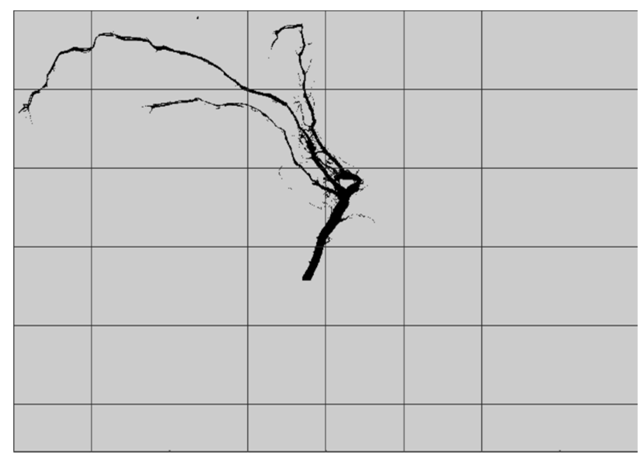
A FRACTAL IS A SHAPE THAT CAN'T BE DESCRIBED BY THE USUAL GEOMETRIC TERMS

- For example, what shape is a plant's root?
- More importantly, how do you measure a plant's root?

FRACTALS AREN'T MEASURED BY CONVENTIONAL METHODS

- We can use something called a "box count"
- We count how many squares in grids of different sizes the fractal occupies.
- As the grid gets smaller, the number of squares occupied gets bigger exponentially!





Ten different contours

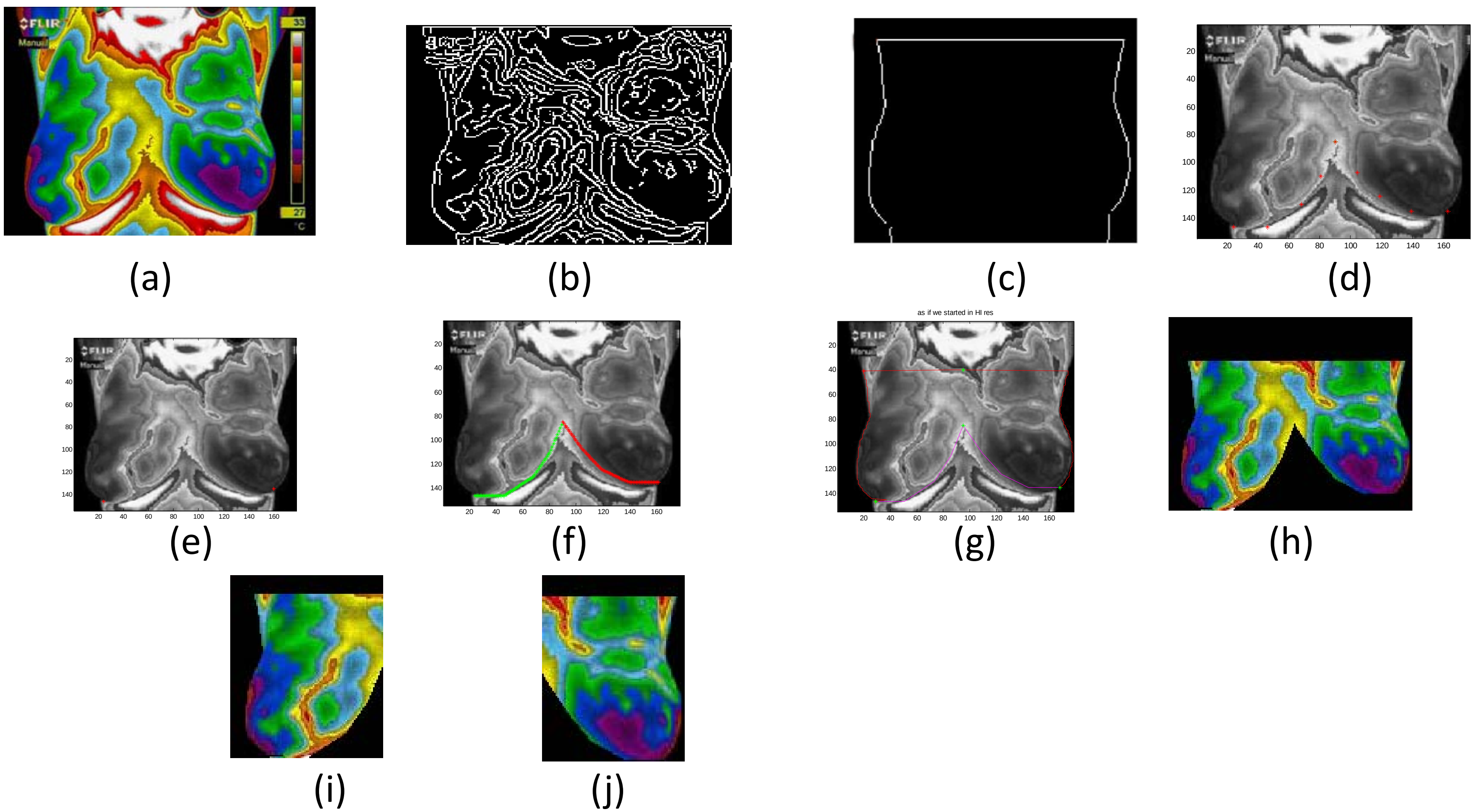
(1) (2) (3) (4) (5)

(6) (7) (8) (9) (10)

Fractal Dimension of Ten different contours

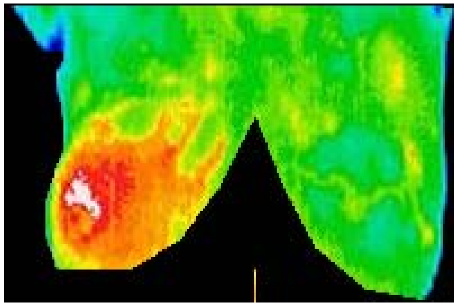
Shape	1	2	3	4	5	6	7	8	9	10
FD	1.0711	1.1573	1.2162	1.2204	1.2750	1.2962	1.4076	1.4194	1.4370	1.4464

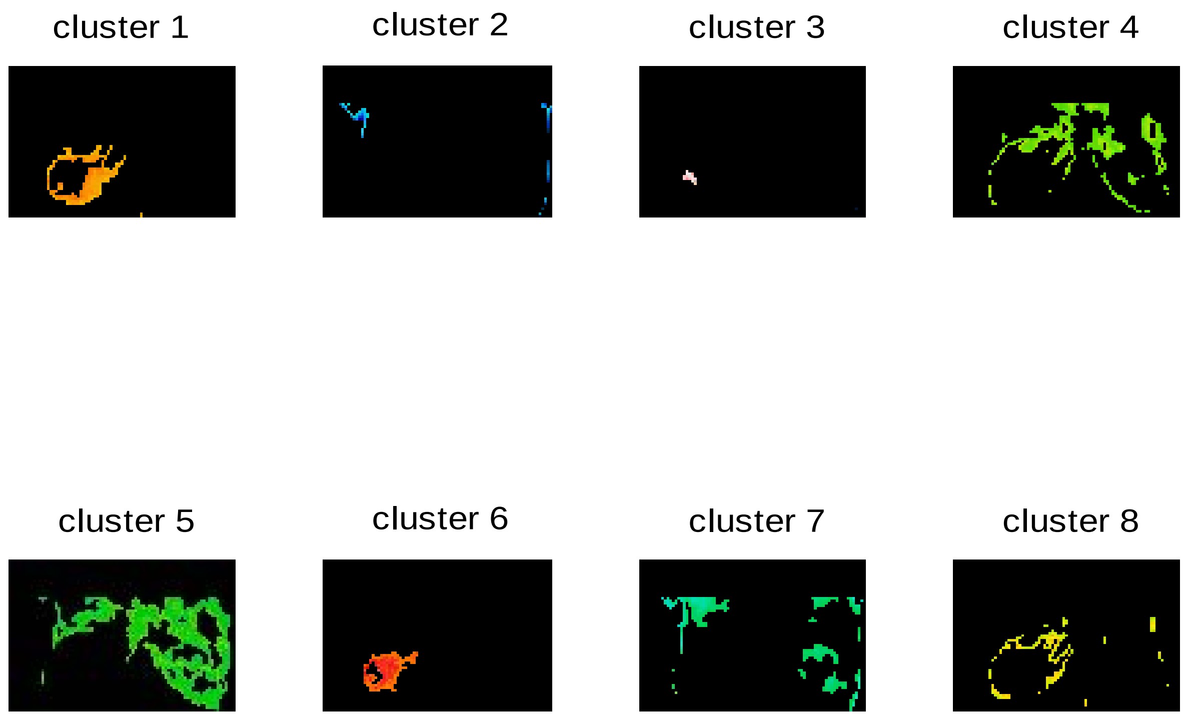
Automatic segmentation of two breasts



(a) Original image, (b) output of canny edge detector, © Extracting outer boundaries
(d) 9 points with equal distances (e) two points with maximum curvature
(f) two lower boundaries (g) all boundaries (h) Extracting two breasts
(i) left breast (j) right breast

Color segmentation by Fuzzy c means





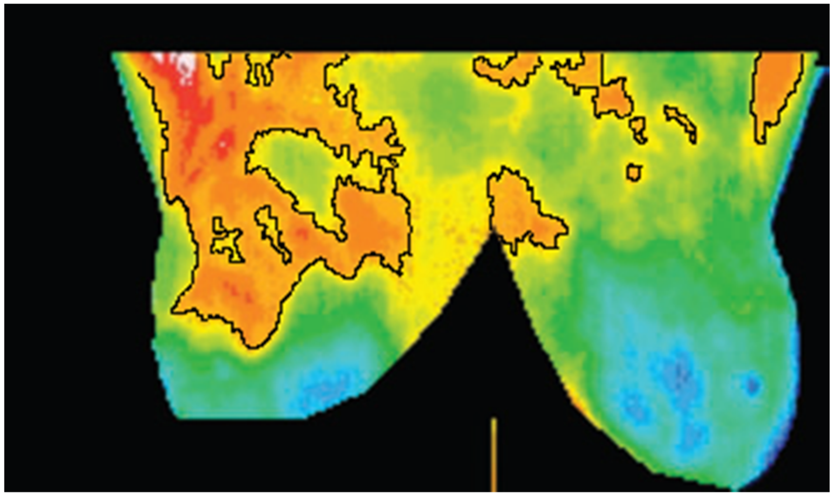
Algorithm for detecting malignancy or benignity of breast tumors by estimating Fractal dimension

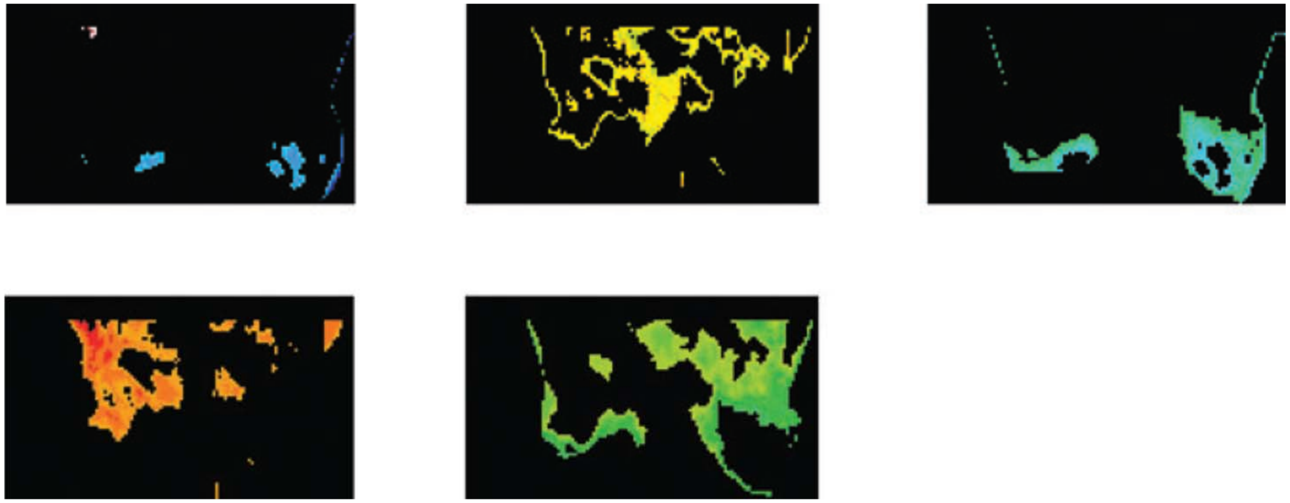
1)The breast IR images are segmented by fuzzy c-means
2) The first hottest regions are identified
The axilla and close sternal boundaries are removed and are not considered.
3) The fractal dimension of step (2) is calculated with Box Counting method

Box Counting method

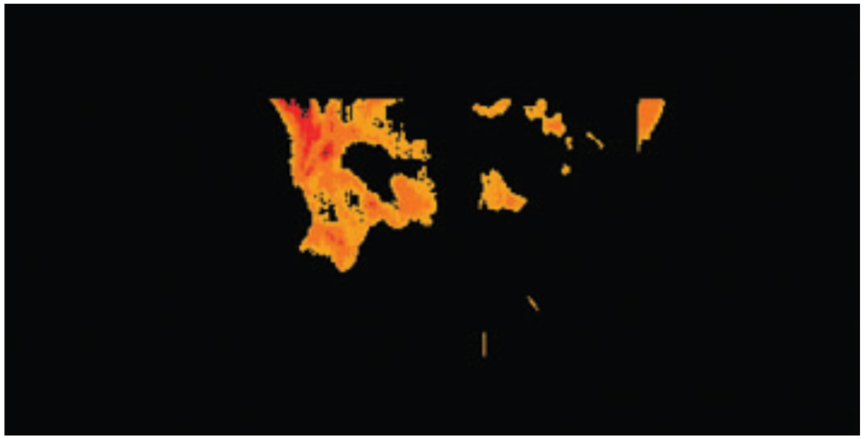
- Making the image of the first hottest regions in binary.
- Detecting the edges.
- Setting up a grid of boxes.
- Counting the number of occupied boxes.
- Changing the boxes sizes and repeating the previous step.
- Calculating the slope of the best fitting line to the plot of the log of the number of box count vs. the log of the number of boxes.

Example

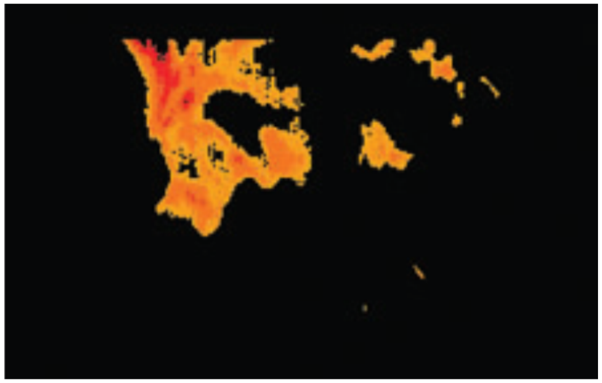




Segmentation by fuzzy c-mean



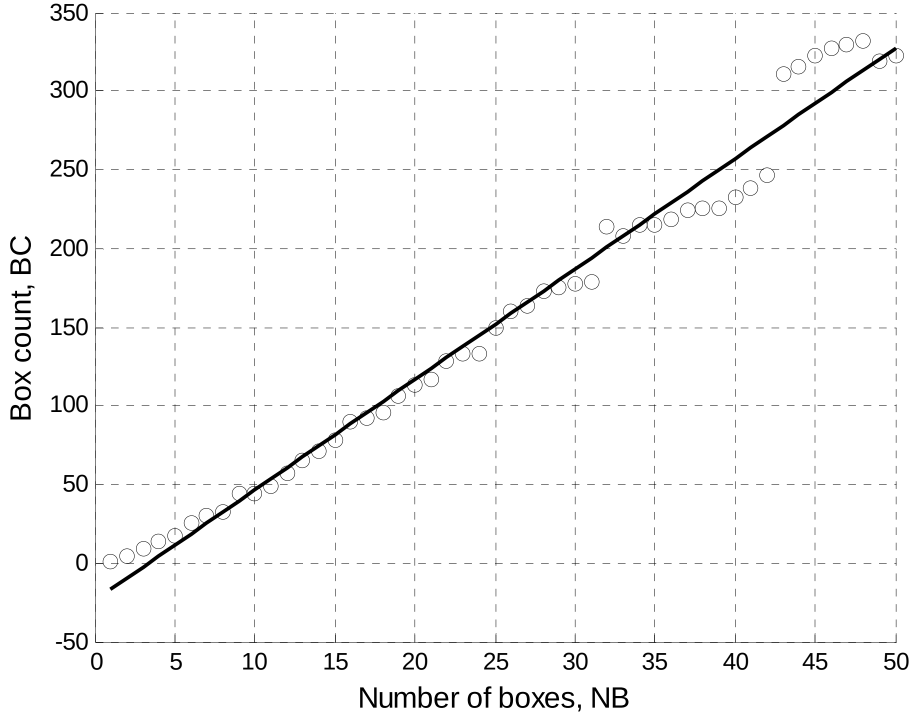
The first hottest regions

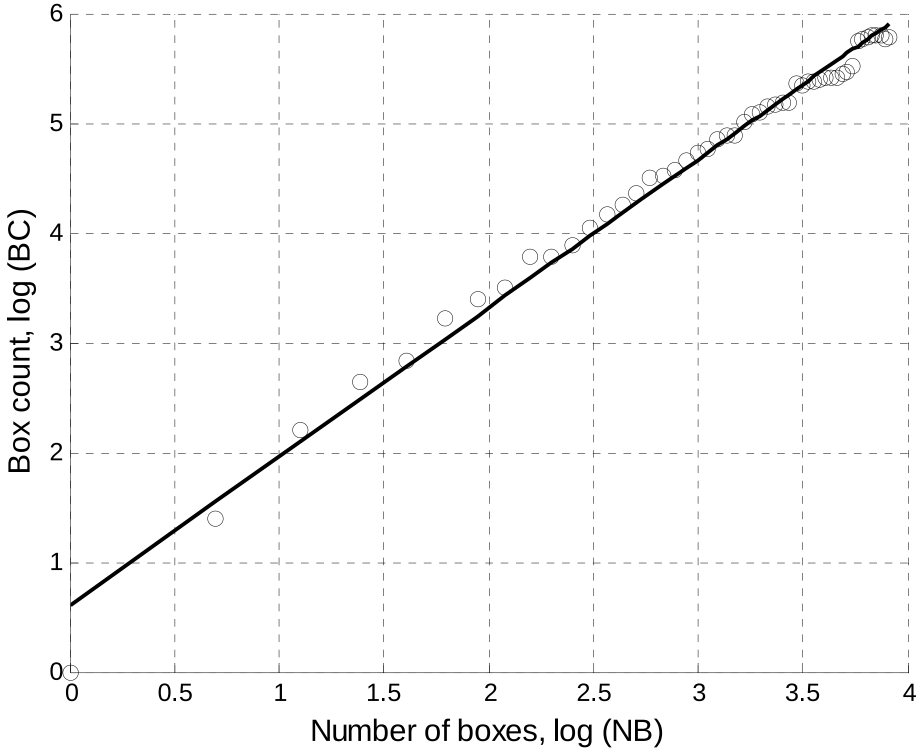


(1)

(2)

(1) The first hottest regions after removing the axilla boundaries
(2) Boundaries of part (1)





(1)

(2)

(1) Box count (BC) vs. number of boxes (NB). (2) log(BC) vs. log (NB).

When was fractals and chaos first researched?When was chaos theory relating to biology first researched?

•Chaos theory relating to biology was first researched in the early 70’s.

• Researchers were looking at how chaos theory could be used to model population trends.

•Several researchers, such as George Oster, Robert May, and Jim Yorke, looked at equations such as this one in their effort to model population:

$$X_{t+1} = l.x_t(1 - x_t)$$

- As for human biology, shortly after the Mandelbrot Set was discovered this also took off.
- Dynamical diseases, a term coined in this era, described diseases that show chaotic systems.
- Researchers such as Leon Glass and Michael Mackey did research in this field.

Cancer Can Grow Unpredictably

•Although cancer appears to develop in an organized fashion when viewed from the outside,

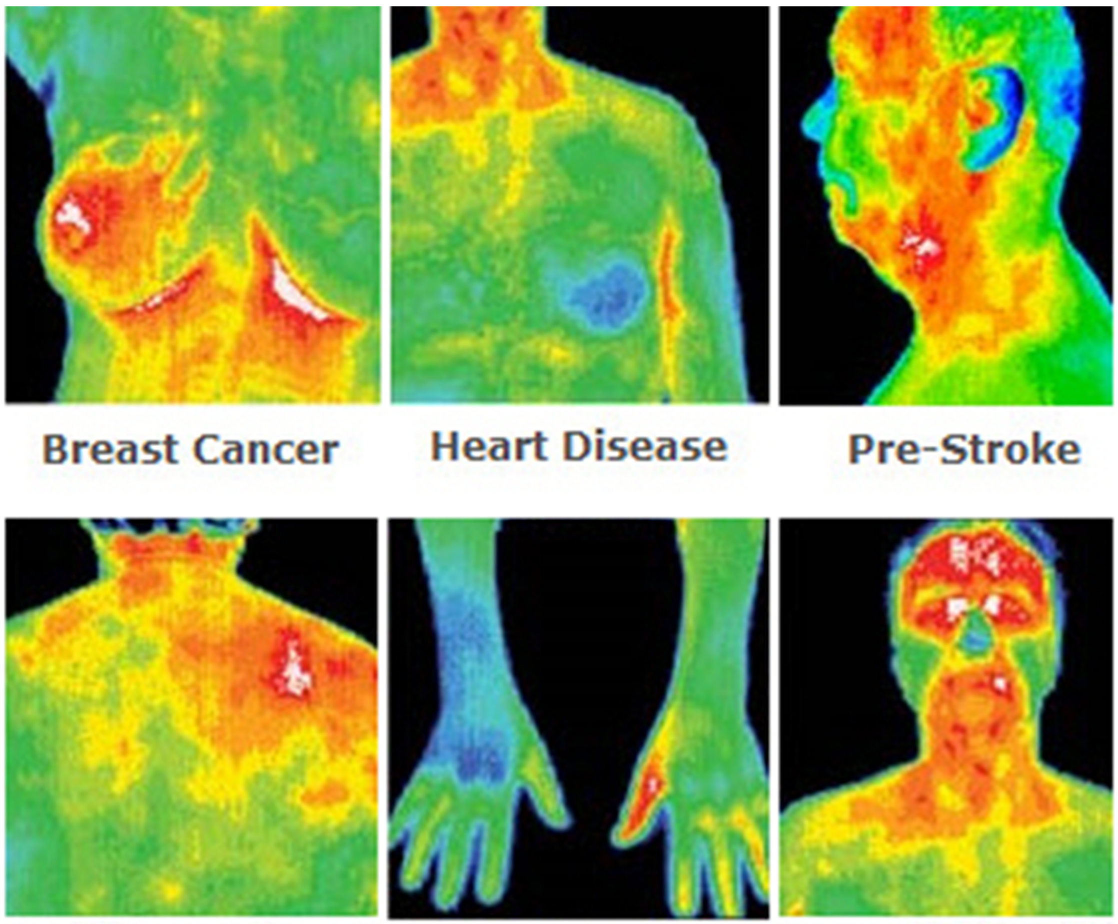
• if we were to go inside a tumor with a little magnifying glass and monitor the movement of cells and the integrity of DNA,

•we would see a much more chaotic situation.

•When the first cancer cell duplicates itself to make two cells, it also duplicates its DNA, which gets passed on to its offspring.

• As two cells become four and so on to generate the billionth cancer cell, the same DNA is duplicated over and over again (remember, a one-centimeter growth contains a billion cells).

•BUT (this is an important but!), DNA does not remain exactly the same over the lifetime of a cancer



Breast Cancer | Heart Disease | Pre-Stroke

Inflammation | Carpal Tunnel | Periodontal

Tumors and other diseases are easily treated with early detection.

90 days:	2 cells
1 year:	16 cells
2 years:	256 cells (tumor size of grain of rice) ▶ **Detectable by Thermal Imaging**
3 years:	4,896 cells
4 years:	65,536 cells
5 years:	1,048,576 cells
6 years:	16,777,216 cells
7 years:	268,435,456 cells ▶ **Detectable by Mammography**
8 years:	4,294,967,296 cells

- As a cancer develops and grows, the DNA that guides it along is prone to change.
- Although the billionth cell is quite similar to the first cell (and would look the same to the pathologist under the microscope),
- its DNA may have more mutations than the first cell; because DNA determines the functions of every cell, the billionth cell may have different physical properties than the first cell.
- Thus, as a cancer grows, its genetic makeup becomes diversified, which leads to a diversity of cell types within it.
- cancer is not a collection of identical cells

•The tendency of a cancer to generate cells with different capabilities explains many of the dreadful aspects of cancer that patients find so hard to grapple with:

- why it can spread from one location to another,
- why it stops responding to a treatment that was working, and
- why it can return when it was in remission.

•The reason is that every cancer, whether it arises in the lung, breast, prostate, bone marrow, fat, or elsewhere, contains different populations of cells that have distinct properties.

Stated another way, the growth of a cancer from one mutant cell is not like putting the original cell on a photocopier, setting the copy number to one billion, and walking away. A cancerous tumor, in fact, does not contain billions of identical clones. Cancer could never develop in this way because it must avoid the immune system's attack on it, live in areas of low oxygen tension, and compete with the rest of the body for vital nutrients. As these conditions change in the body, a cancer must adapt; if it fails to adapt, it is eliminated

Waldrop describes *chaos* as a nonlinear phenomenon [where]…a tiny event over *here* can have an enormous effect over *there*…the flap of a butterfly's wings in Texas could change the course of a hurricane in Haiti a week later…everything is connected and often with incredible sensitivity. Tiny perturbations won't always remain tiny. Under the right circumstance [and critical timing], the slightest uncertainty can grow until the system's future becomes utterly unpredictable…chaotic…[a] pattern of ever-increasing [disorganized] complexity

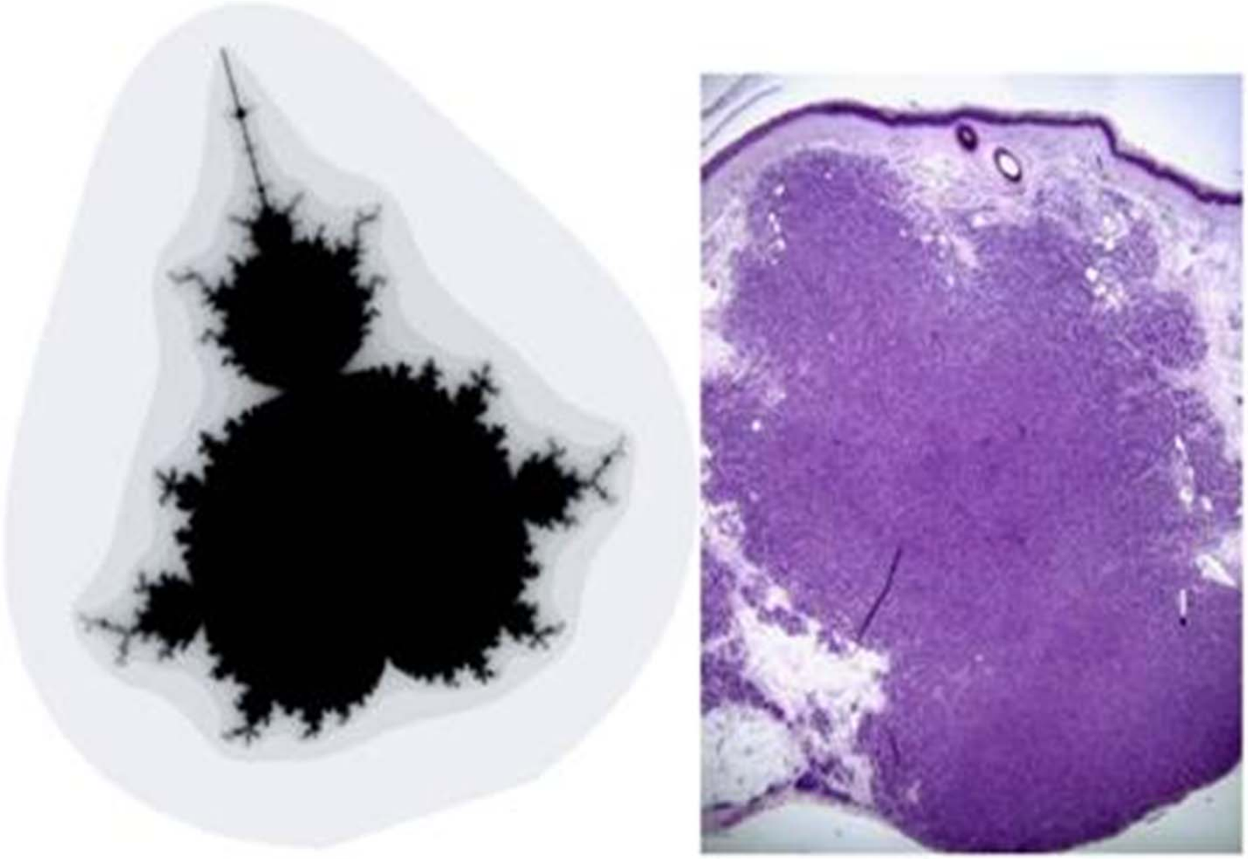
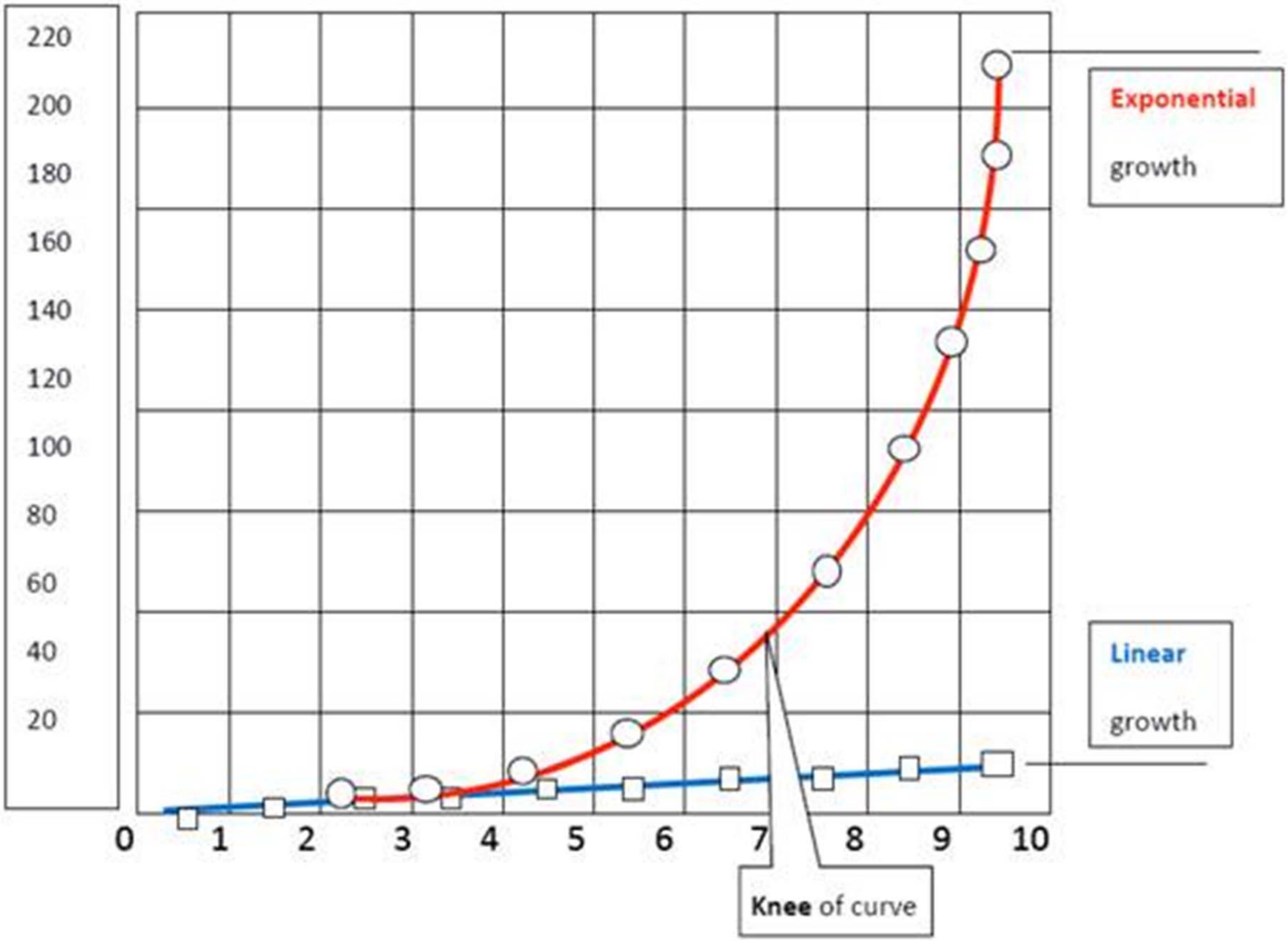


Fig. On the left is a classic Mandelbrot geometric pattern not unlike Merkel cell carcinoma on the right (local.wasp.uwa.edu.au/.../fractals/fracintro/ and http://path.upmc.edu/cases/case398.html respectively)

Chaos is characterized by exponential iterations with a potential for runaway growth acceleration

. A graphic comparison of a positive exponential curve with a linear line can express the relationship between normal and malignant growth



Adopted from Kurzweil

http://www.medsci.org/v04p0164.htm

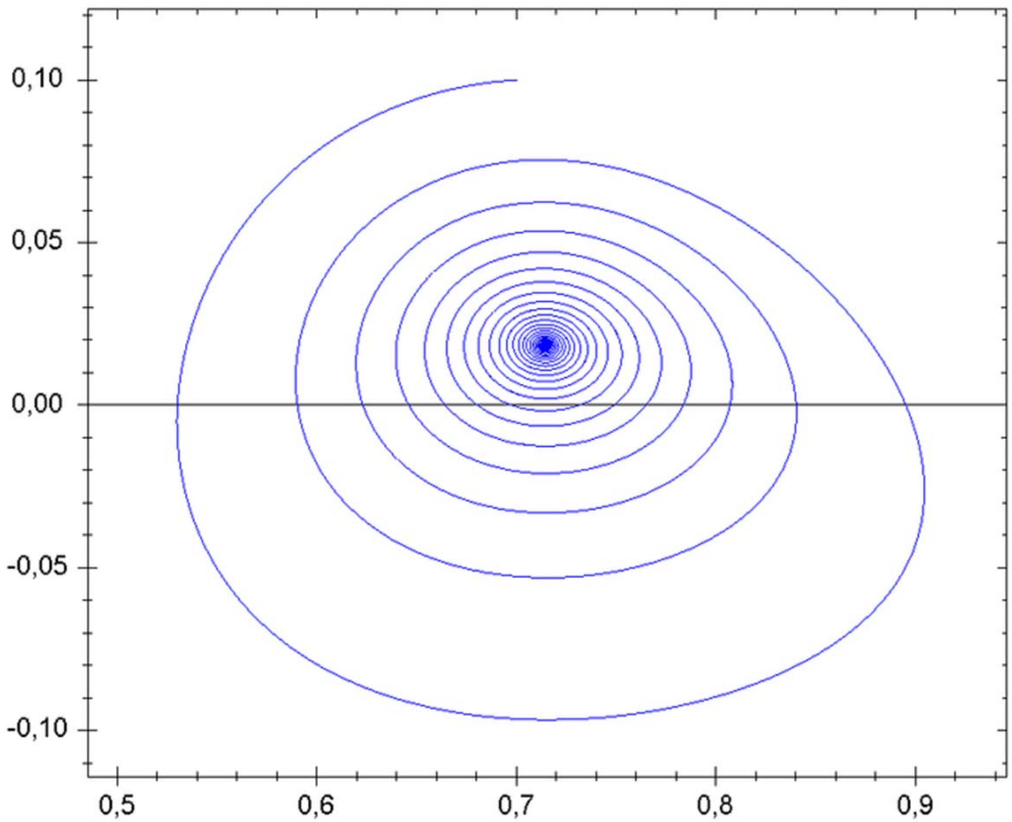
Cancer is a significant medical and societal problem. This reality arises from the fact that an exponential and an unrestricted cellular growth destabilizes human body as a system. From this perspective, cancer is a manifestation of a system-in-failing.

Cancerous cells, tumors, and vasculature defy have irregular shapes which have potential to be described by a nonlinear dynamical system.

- Chaotic time series (CTS) could provide the tools necessary to generate the procedures to evaluate the nonlinear system.
- Computing Lyapunov exponents (LEs) is a powerful means of quantifying the degree of the chaos.

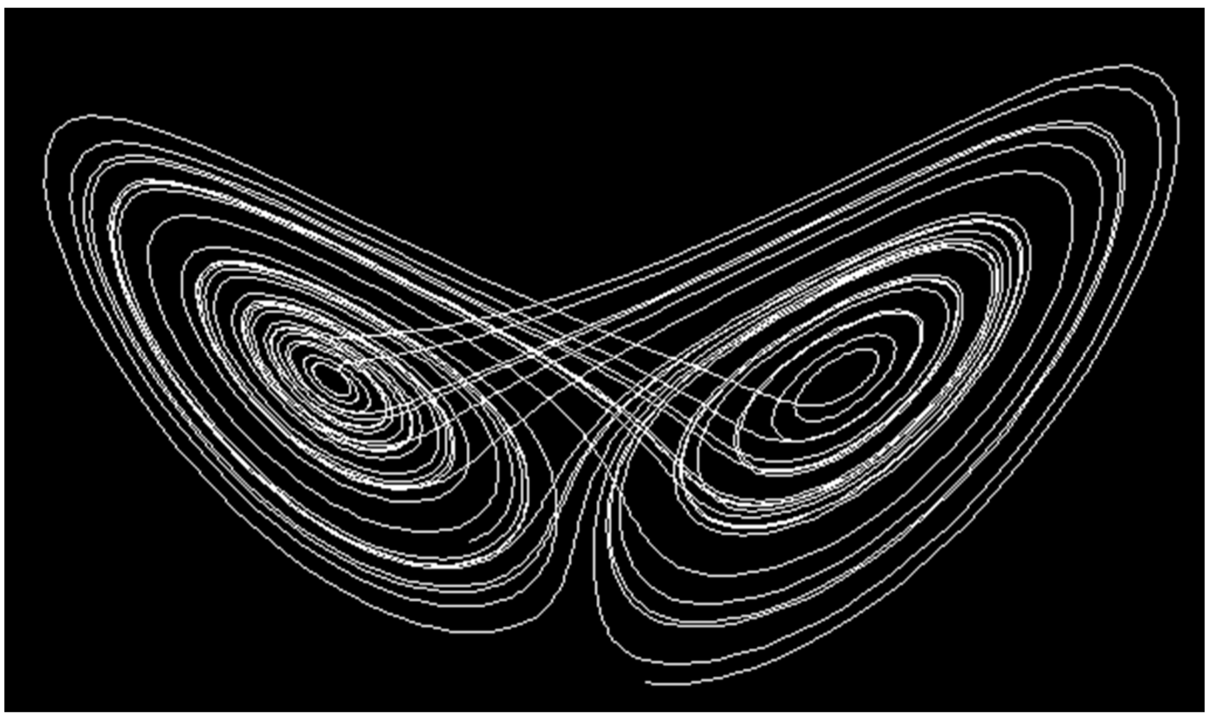
- The basic idea of CTS analysis is that an unknown complex system can be described by a strange attractor in its PS, and
- it is important to reconstruct the system state-space starting from observed time series.
- The observed time series can be seen as the output of an unknown system corrupted by noise.

A phase space, introduced is a space_in which all possible states of a system are represented, with each possible state of the system corresponding to one unique point in the phase space.



Phase space of a dynamical system with focal stability

In 1961, meteorologist **Edward Lorenz** (1917-) found that extremely small changes in initial conditions had a significant effect on the weather



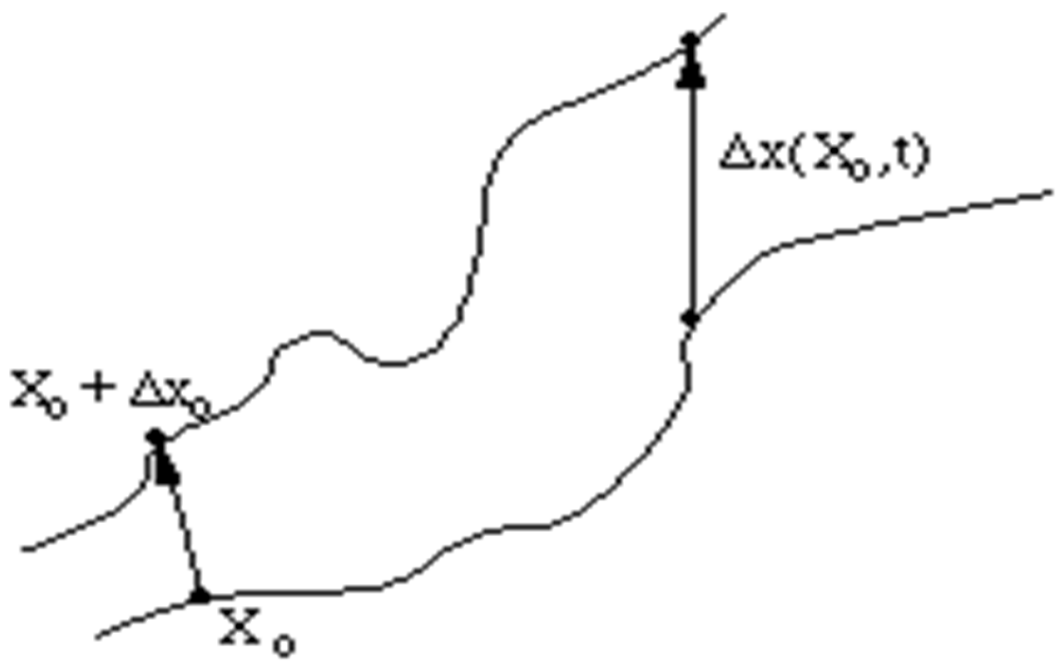
•We do not have full knowledge of the dynamics of the system because we do not have measurements for each possible variable in the system

• However, in practice, we usually have only one TS measurement. In such cases, though we cannot find the exact PS of the system, a pseudo PS (equivalent to the original PS in terms of the system invariants) may still be constructed.

•This pseudo PS is called the reconstructed phase space (RPS)

Lyapunov exponents (LE)

The sensitive dependency on the initial conditions can be measured by LEs. It is the averaged rate of divergence or convergence of two neighboring trajectories in the PS.

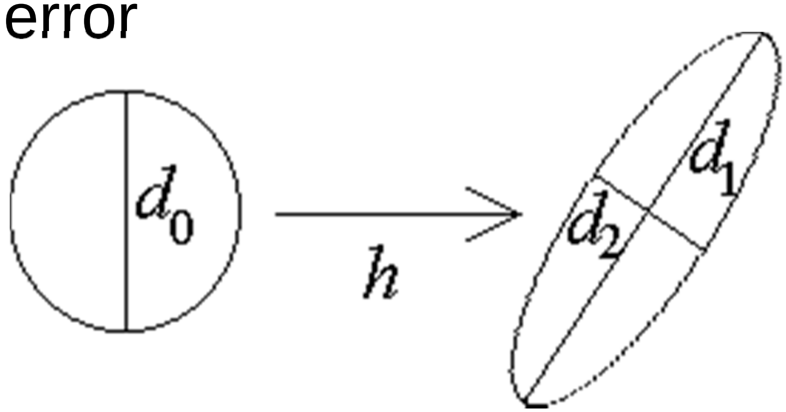


•With a continuous dynamical system in *n* dimensional PS,

•we monitor the long term evolution of an infinitesimal *n* sphere initial condition where *n* is the number of equations (or equivalently, the number of state variables) used to describe the system.

• As time (*t*) progresses, the sphere evolves into an ellipsoid whose principle axes expand (or contract) at rates given by the LEs.

•By comparing an orbit belonging to some initial condition with an orbit for an initial condition which carries an error

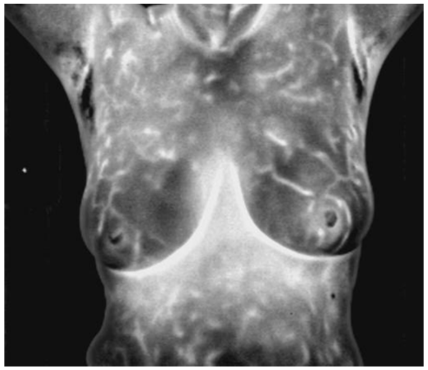


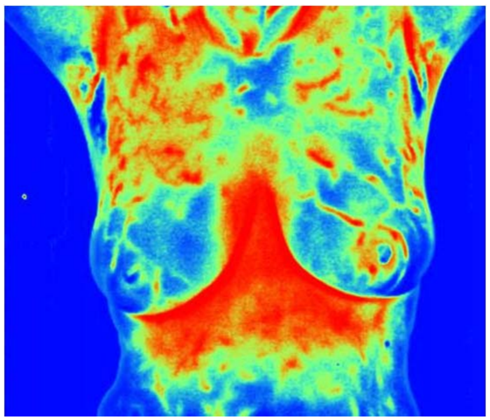
The Lyapunov exponent (LE) characterizes the average logarithmic growth of the relative error per iteration

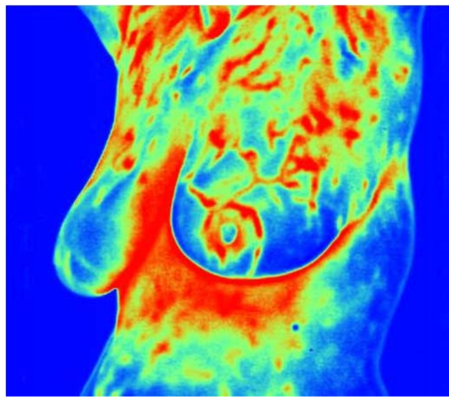
Zero exponents indicate that the system is in some sort of steady state mode

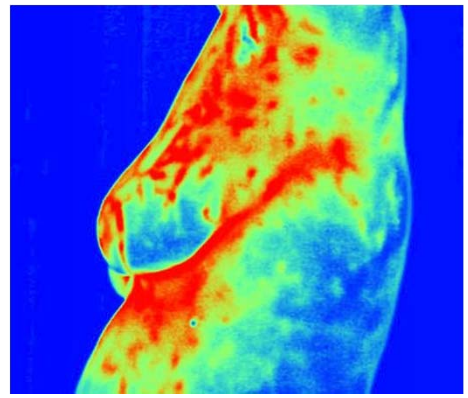
while the positive ones indicate that the system is chaotic.

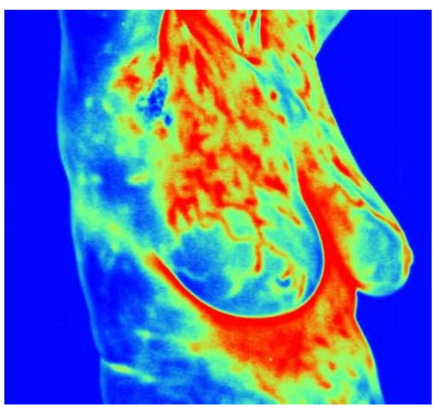
Data Collection in Seyedo Shohada Hospital in Isfahan

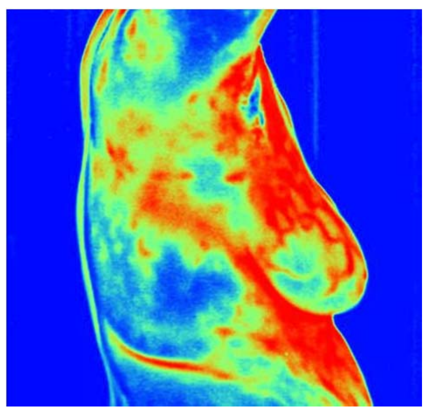






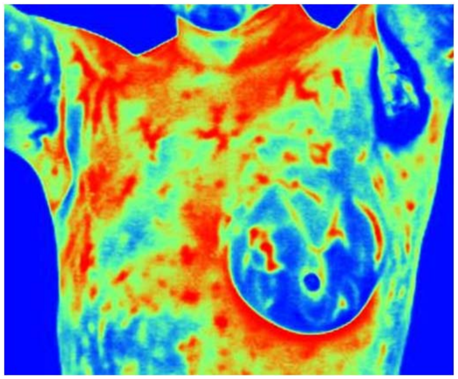
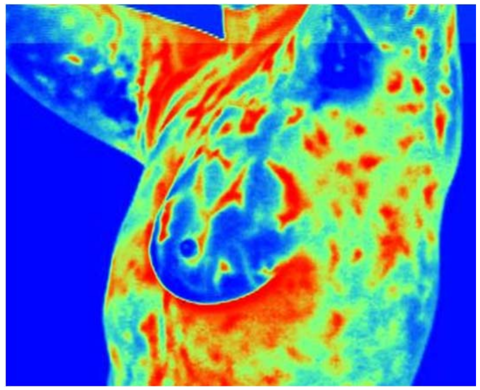
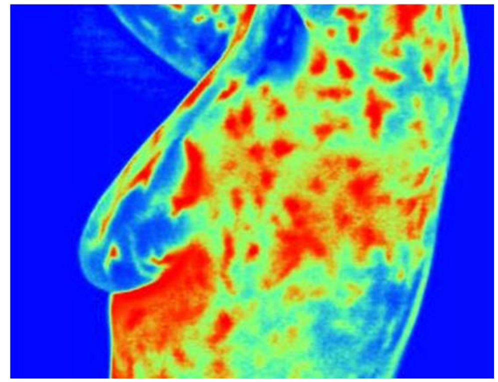
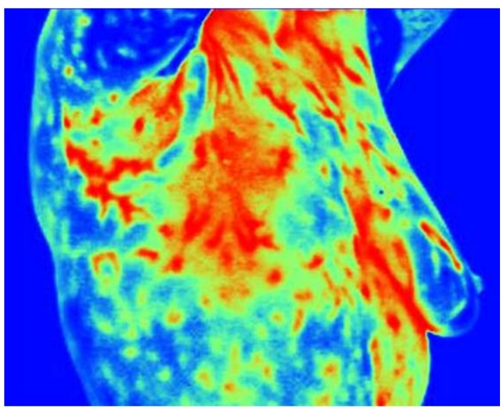
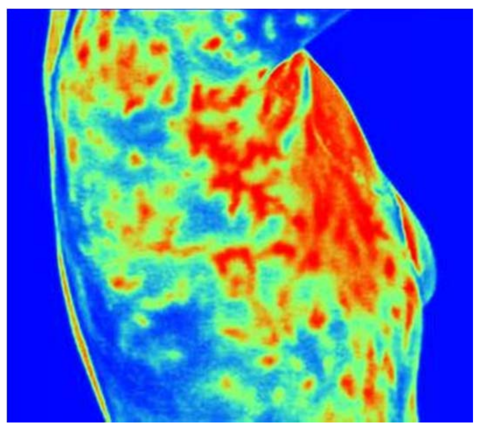






- Camera resolution 0.01 degree centigrade
- better room condition

Data Collection in Seyedo Shohada Hospital in Isfahan (second time)


Thank you for your
attention