

CLASSIFICATION OF ULTRASOUND IMAGES REGARDING FEATURES ASSOCIATED WITH FOLLICLES USING BINARY HYPOTHESIS TECHNIQUE AND SUPPORT VECTOR MACHINE METHOD

MADHURI M

Research Scholar, Dept of CSE, ANU, AP, India.

Prof. L S S REDDY

Professor, Dept of CSE, KLU, AP, India

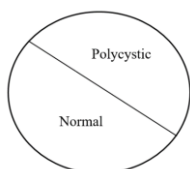
Abstract

This paper explains the commonsense technique to characterize ultrasound polycystic symbolisms dependent on the shape highlights of follicular sores. On a considerably basic level, arrangement alludes to design acknowledgment. For this situation, designs are shape highlights of follicular growths. The elements of the pimples add up to their sizes. Contingent upon the size of blisters and number of sores, an ovary could be delegated polycystic.

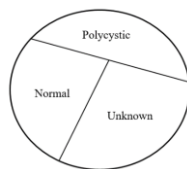
Keywords: Polycystic, Cysts, Hypothesis, Vector, Classification.

Introduction

In Binary Hypothesis Testing, the basic part of arrangement in this setting is to get (i) number of sores and (ii) their sizes. These two boundaries are very adequate to perceive a picture as either polycystic or ordinary. The perception class at that point comprises of two classifications (I) polycystic ovaries and (ii) typical ovaries. Fig. 1 shows such a perception space as parceled sets.



Observation space for binary hypothesis



Observation space for ternary hypothesis

Fig. 1: Observation space

This twofold grouping may flop now and again on account of the idea of ultrasound pictures accessible close by. Reasons are

numerous however basically it is because of filtering by untalented expert or because of inferior quality scanner, which may present shading clamor and spot commotion. In such circumstances, one may go in for ternary characterization of perception space, for example, (I) polycystic ovaries, (ii) ordinary ovaries and (iii) obscure kind of ovaries, which are appeared in Fig. 1.

The extent of this paper is restricted to double speculation and henceforth, a hypothetical establishment for twofold theory testing is given in the following segment. In this unique circumstance, the hypothetical detailing is as per the following.

Binary Hypothesis Classification

Binary perception space is isolated into H1 and H0. L(y) is the anticipated yield file and it is either a 1 or a 0. Double speculation testing is a solo testing technique by excellence of which one can choose whether a given ultrasound picture speaks to a polycystic ovary or not. Two sorts of approaches are being used (I) traditional probabilistic methodology and (ii) deterministic methodology. The two methodologies depend on at least one highlights of the picture under test. In any case, the extent of this paper is restricted to order dependent on a solitary boundary 'follicle size and number of pimples'. A hypothetical establishment for the

probabilistic methodology is given underneath.

Binary Hypothesis Testing - Decision Rule

Binary hypothesis problem

Let us indicate the 'choice of an ovary is typical' by H_0 and the 'choice of an ovary is polycystic' by H_1 . Either H_0 ought to be valid or H_1 ought to be valid as the aftereffect of characterization. Choice principles will have three yields (I) H_0 valid, (ii) H_1 valid, (iii) don't have the foggiest idea.

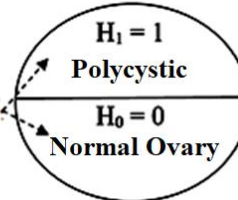
Consequently, every time the investigation is directed one of four things can occur. Table 1 lists out the four possibilities.

Table 1 Decision possibilities

Sl. No	Decision	Remarks
1	H_0 true; choose H_0	Right Decision
2	H_0 true; choose H_1	Wrong Decision

3	H_1 true; choose H_1	Right Decision
4	H_1 true; choose H_0	Wrong Decision

The basic probabilistic model of binary hypothesis testing is given below.

$$L(y) \triangleq \frac{P(y|H_1)}{P(y|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \tau$$


where $L(y)$ is the anticipated yield record, $P(y|H_1)$ is the restrictive likelihood of the occasion y given H_1 as from the earlier data, $P(y|H_0)$ is the contingent likelihood of the occasion y given H_0 as from the earlier data, τ is a picked limit dependent on the component vector, H_1 compares to the polycystic ovary, in a zone and H_0 relates to ordinary ovary. In the instances important to us, we don't know which theory is valid.

The second segment of the issue is a probabilistic progress system; the third is a perception

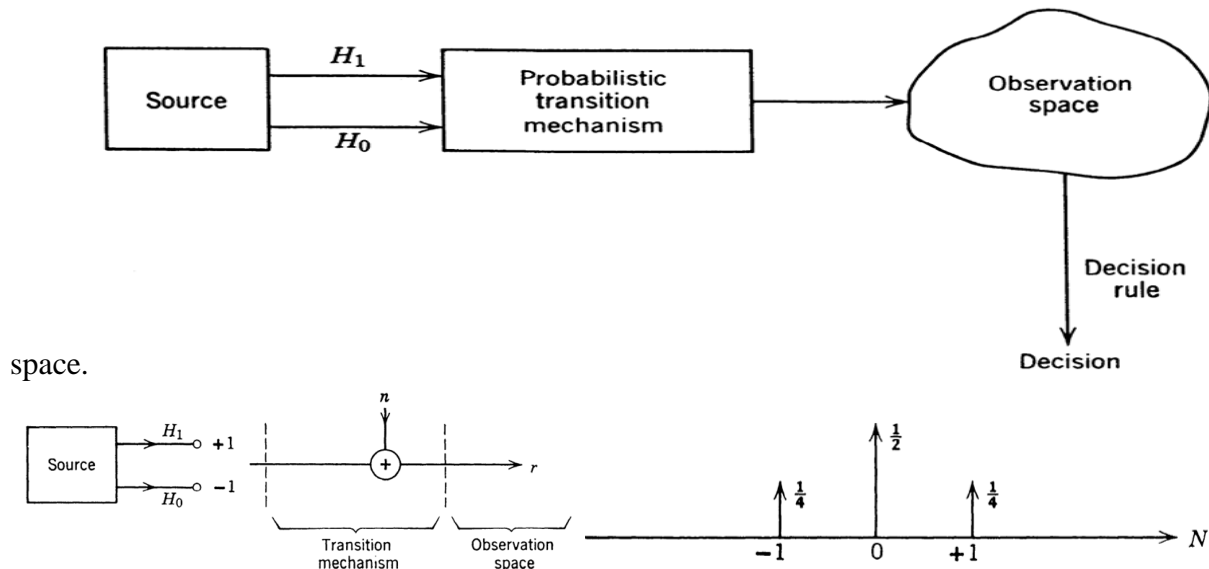


Fig. 2: Probabilistic transition mechanism and observation space.

Formulation of decision rule

Binary hypothesis problem

As said before, either H_0 ought to be valid or H_1 ought to be valid. Choice guidelines will have three yields (a) H_0 valid, (b) H_1

valid, (c) don't have a clue. Subsequently each time the investigation is led one of four things can occur (i) H_0 valid; pick H_0 , (ii) H_0 valid; pick H_1 , (iii) H_1 valid; pick H_1 and (iv) H_1 valid; pick H_0 . On this, one can lead Bayes test. A Bayes test is based on two assumptions.

1. Source outputs are governed by probability assignments, which are denoted by P_1 and P_0 , respectively, and called the a priori probabilities.
2. A cost is assigned to each possible course of action like C_{00} , C_{10} , C_{11} , C_{01} . The first subscript indicates the hypothesis chosen and the second, the hypothesis that was true.
3. Expected value of the cost is viewed as **risk**
4. $R = C_{00}P_0\Pr(\text{say } H_0 \mid H_0 \text{ is true}) + C_{10}P_0\Pr(\text{say } H_1 \mid H_0 \text{ is true}) +$

$$C_{11}P_1\Pr(\text{say } H_1 \mid H_1 \text{ is true}) + C_{01}P_1\Pr(\text{say } H_0 \mid H_1, \text{ is true})$$

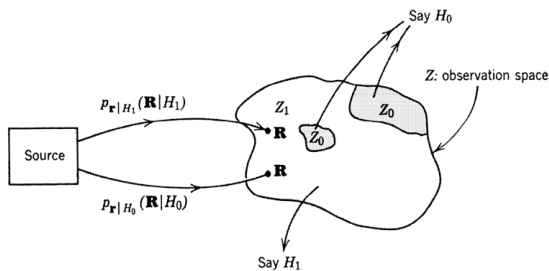


Fig. 3: Decision rule mechanism
 The decision rule must say either H_1 or H_0 . The rule divides the total observation space Z into two parts, Z_0 and Z_1 . Whenever an observation falls in Z_0 we say H_0 , and whenever an observation falls in Z_1 we say H_1 . Note that for an N -dimensional observation space the integrals would be N -fold integrals. Now,

the risk in terms of the transition probabilities and the decision regions is

$$\begin{aligned}
 \mathcal{R} &= C_{00}P_0 \int_{Z_0} p_{\mathbf{r}|H_0}(\mathbf{R}|H_0) d\mathbf{R} \\
 &+ C_{10}P_0 \int_{Z_1} p_{\mathbf{r}|H_0}(\mathbf{R}|H_0) d\mathbf{R} \\
 &+ C_{11}P_1 \int_{Z_1} p_{\mathbf{r}|H_1}(\mathbf{R}|H_1) d\mathbf{R} \\
 &+ C_{01}P_1 \int_{Z_0} p_{\mathbf{r}|H_1}(\mathbf{R}|H_1) d\mathbf{R}
 \end{aligned}$$

$$\begin{aligned}
 \mathcal{R} &= P_0C_{00} \int_{Z_0} p_{\mathbf{r}|H_0}(\mathbf{R}|H_0) d\mathbf{R} + P_0C_{10} \int_{Z-Z_0} p_{\mathbf{r}|H_0}(\mathbf{R}|H_0) d\mathbf{R} \\
 &+ P_1C_{01} \int_{Z_0} p_{\mathbf{r}|H_1}(\mathbf{R}|H_1) d\mathbf{R} + P_1C_{11} \int_{Z-Z_0} p_{\mathbf{r}|H_1}(\mathbf{R}|H_1) d\mathbf{R} \\
 \int_Z p_{\mathbf{r}|H_0}(\mathbf{R}|H_0) d\mathbf{R} &= \int_Z p_{\mathbf{r}|H_1}(\mathbf{R}|H_1) d\mathbf{R} = 1 \\
 \mathcal{R} &= P_0C_{10} + P_1C_{11}
 \end{aligned}$$

$$\begin{aligned}
 &+ \int_{Z_0} \{ [P_1(C_{01} - C_{11})p_{\mathbf{r}|H_1}(\mathbf{R}|H_1)] \\
 &- [P_0(C_{10} - C_{00})p_{\mathbf{r}|H_0}(\mathbf{R}|H_0)] \} d\mathbf{R}.
 \end{aligned}$$

$$\begin{aligned}
 P_1(C_{01} - C_{11})p_{\mathbf{r}|H_1}(\mathbf{R}|H_1) &\geq P_0(C_{10} - C_{00})p_{\mathbf{r}|H_0}(\mathbf{R}|H_0) \\
 \frac{p_{\mathbf{r}|H_1}(\mathbf{R}|H_1)}{p_{\mathbf{r}|H_0}(\mathbf{R}|H_0)} &\underset{H_0}{\overset{H_1}{\geq}} \frac{P_0(C_{10} - C_{00})}{P_1(C_{01} - C_{11})}
 \end{aligned}$$

$$\Lambda(\mathbf{R}) \triangleq \frac{p_{\mathbf{r}|H_1}(\mathbf{R}|H_1)}{p_{\mathbf{r}|H_0}(\mathbf{R}|H_0)}$$

$$\eta \triangleq \frac{P_0(C_{10} - C_{00})}{P_1(C_{01} - C_{11})}$$

$$\Lambda(\mathbf{R}) \underset{H_0}{\overset{H_1}{\geq}} \eta$$

The outcome empowers us to assemble the whole processor and leave \square as a variable limit to oblige changes in our evaluations of from the earlier probabilities and expenses.

Practically speaking, one would like to work with a deterministic methodology, which would make the employment simpler and vigorous. Subsequently, a

methodology is acquainted in this segment with arrange polycystic pictures from ordinary pictures, which is basically a paired speculation testing. Before diving into subtleties, it is smarter to have an

unmistakable understanding regarding how to organize 'highlight vectors' of ultrasound ovary pictures that are given as contributions to a more tasteful like Support Vector Machine (SVM).

Follicular Size Evaluation and Feature Vector

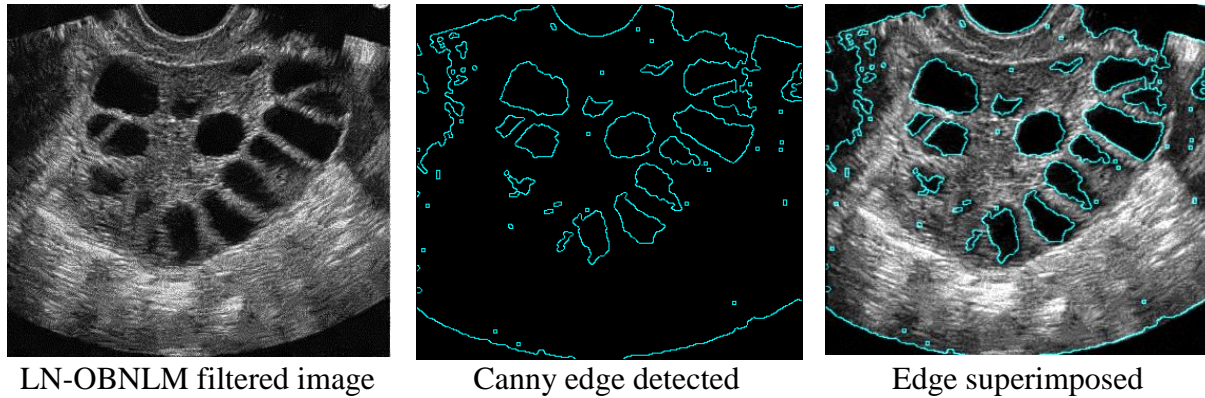


Fig. 4: Input image and Canny edge detected version

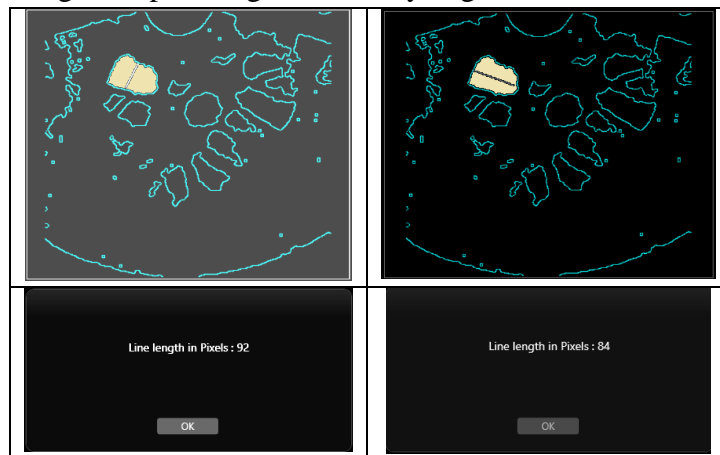


Fig. 5: Selected cyst and its dimensions

Now, approximate size of the cyst = $92 \times 84 = 7728$ square pixel units

Number of cysts in the image = 18

Dominant follicles = 3

Medium size cysts = 7

Small size cysts = 8

Feature vector

Number of cysts	Number of small size cysts	Number of middle size cysts	Number of middle size follicles	Size of the dominant follicle
18	8	7	3	7728 square pixel units

There are five segments in the element vector. There is no compelling reason to utilize every one of the five parts for arrangement. On the off chance that the information base is too huge having intently comparative pictures, at that point it is needed to utilize each of the five segments of the component vector. Else, one can utilize only a couple of segments for grouping. Fig. 5 shows a polycystic ultrasound ovary picture. A conventional grouping strategy like Support Vector Machine (SVM) is used to classify images on a free running mode. Basic working principles of Support Vector Machine (SVM) classifier is briefly explained below.

Basics of Support Vector Machines

SVMs structure another age learning calculations. During 1980's, learning calculations were versatile to direct choice surfaces. Such calculations depended on solid hypothetical establishments and they have apparent hypothetical properties. As respect nonlinear choice surfaces, then again, choice trees and neural organizations (NNs) were utilized for AI. Sadly, such strategies experienced absence of hypothetical establishments and furthermore from neighborhood minima and accordingly ideal arrangements are not commonly expected to take care of an issue. During 1990s, powerful learning calculations for fathoming nonlinear

capacities were created, which displayed great hypothetical properties.

On the Notion of Support Vector Machines

Support Vector Machine (SVM) is basically a one layer or multi-layer neural organization. The quantity of layers relies upon the calculation. SVM could be applied to designs that are directly distinct. Obviously, it very well may be applied to nonlinearly distinct examples too by reasonable planning unique information into new space, which is known as 'part work'. SVM is basically a calculation utilized for design acknowledgment. Backing vectors are the information focuses that lie exceptionally near the choice surface, which is additionally called 'hyper plane'.

Input – Output Relationships

Much the same as what is done on account of neural organizations, the preparation test highlights x_1, x_2, \dots, x_n are given to SVM as information sources and the yield is chosen as 'y'. Each component can have a weight so the weight vector w_1, w_2, \dots, w_n is related with the info vector. The choice capacity sets an edge and computes 'y' utilizing the equation including the weighted information sources. Along these lines, this is actually similar to what is done in a neural organization.

In this unique circumstance, the element vector that is considered for perceiving polycystic symbolisms is spoken to as:

Number of cysts	Number of small size cysts	Number of middle size cysts	Number of middle size follicles	Size of the dominant follicle
-----------------	----------------------------	-----------------------------	---------------------------------	-------------------------------

One can reduce the number of features of this feature vector depending on the

situation, available database and application requirement.

Support Vector Machine for Classifying Ultrasound Ovary Images

In this an exertion was made to computerize the way toward characterizing polycystic ovary pictures from typical ones utilizing an arranged grouping of tasks finishing with SVM based double order. Fig. 6 shows the square outline of the

grouping of activities associated with the arrangement cycle. Matlab coding has been done for executing this method. This coordinated Matlab code actualizes a wide range of tasks talked about in this proposition and gives adaptability to clients to pick whatever program is wanted.

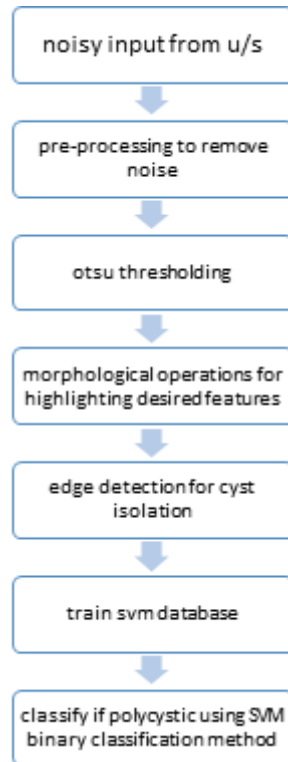
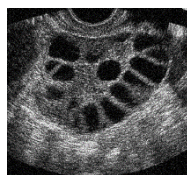
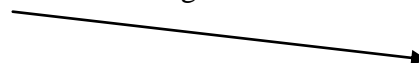


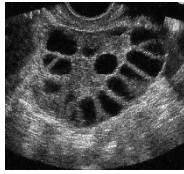
Fig. 6: Sequence of operations in the binary classification using SVM

A sample ultrasound ovary image is considered here to demonstrate the application procedure of the integrated Matlab code developed to classify ovary images. Fig. 7 shows the flowchart.

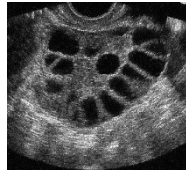


Sample input ultrasound image

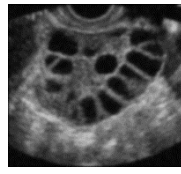




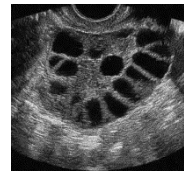
Wiener
filtered image
(open)



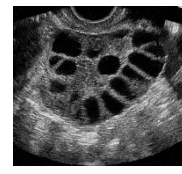
Bilateral
filtered image
(open)



AD filtered
image
(open)



OBNLM
filtered image
(open)



LN-OBNLM
filtered
image
(chosen)



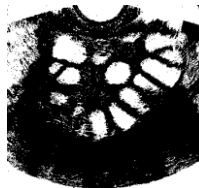
Otsu thresholded



Eroded



Dilated



Negative



Canny edge detected

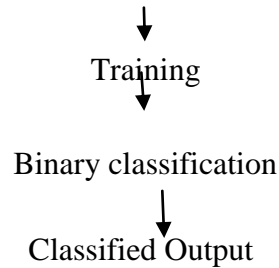


Fig. 7: Flowchart of the classification process right from raw input image

Observations & Conclusion

Parallel arrangement utilizing SVM procedures works out very well on account of dividing an information base comprising of ultrasound ovary pictures into (i) typical ovaries and (ii) polycystic ovaries. The precision of characterization relies upon singular pictures. Debased pictures may offer ascent to 'bogus caution'.

References

1. Mahmoudi, M.; Sapiro, G.: *Fast image and video denoising via nonlocal means of similar neighborhoods*. *IEEE Signal Processing Letters*. 12 (2205) 839-842
2. Portilla, J., Strela, V., Wainwright, M., Simoncelli, E.: *Image denoising using scale mixtures of Gaussians in the wavelet domain*. *IEEE T. Image Process*. 12 (2003) 1338-1351
3. Tomasi, C., Manduchi, R.: *Bilateral filtering for gray and color images*. *ICCV'98, Bombay (1998)*
4. van de Weijer, J., van den Boomgaard, R.: *Local mode filtering*. *CVPR'01, Kauai (2001)*
5. N. Jacob and A. Martin. "Image denoising in the wavelet domain using wiener filtering", *Unpublished course project, University of Wisconsin, Madison, Wisconsin, USA, 2004*.
6. V. Strela, "Denoising via block wiener filtering in wavelet domain", *3rd European Congress of Mathematics, Barcelona, Birkhäuser Verlag, July 2000*.
7. H. Choi and R. G. Baraniuk, "Analysis of wavelet domain wiener filters", *IEEE Int. Symp. Time-Frequency and Time-Scale Analysis, (Pittsburgh), Oct. 1998*.
8. Paris S., Durand F. (2006) *A Fast Approximation of the Bilateral Filter Using a Signal Processing Approach*. In: Leonardis A., Bischof H., Pinz A. (eds) *Computer Vision – ECCV 2006*. *ECCV 2006. Lecture Notes in Computer Science*, vol 3954. Springer, Berlin, Heidelberg
9. R. Vanithamani and G. Umamaheswari, "Performance Analysis of Filters for Speckle Reduction in Medical Ultrasound Images", *International Journal of Computer Applications* 12(6):23–27, December 2010.
10. R. Sivakumar and D. Nedumaran "Comparative study of Speckle Noise Reduction of Ultrasound B-scan Images in Matrix Laboratory Environment", *International Journal of Computer Applications* 10(9):46–50, November 2010.
11. Y. Yongjian and S. T. Acton, "Speckle reducing anisotropic diffusion," *IEEE Trans. Image Processing*, vol. 11, no. 11, pp.1260–1270, Nov. 2002.