

Prof-V.M. Vadre.
Date 03-5-10

TWO APPLICATIONS

(LECTURE 38)

- DATA MINING
- FACE RECOGNITION

Applications of

Wavelets in Data

Mining

Improve the efficiency
of Multilevel Surprise
and Trend Queries

Data Representation

as a Matrix

$$\tilde{X} = M \times N$$

(1) Efficient Storage

(2) Efficient Retrieval

(3) Can be easily modified

Singular Value Decomposition (SVD)

$$\tilde{X} = U \Lambda V$$

$m \times r$ $r \times r$ $r \times n$

$r =$ Rank of Matrix \tilde{X}

(1)

Complexity of

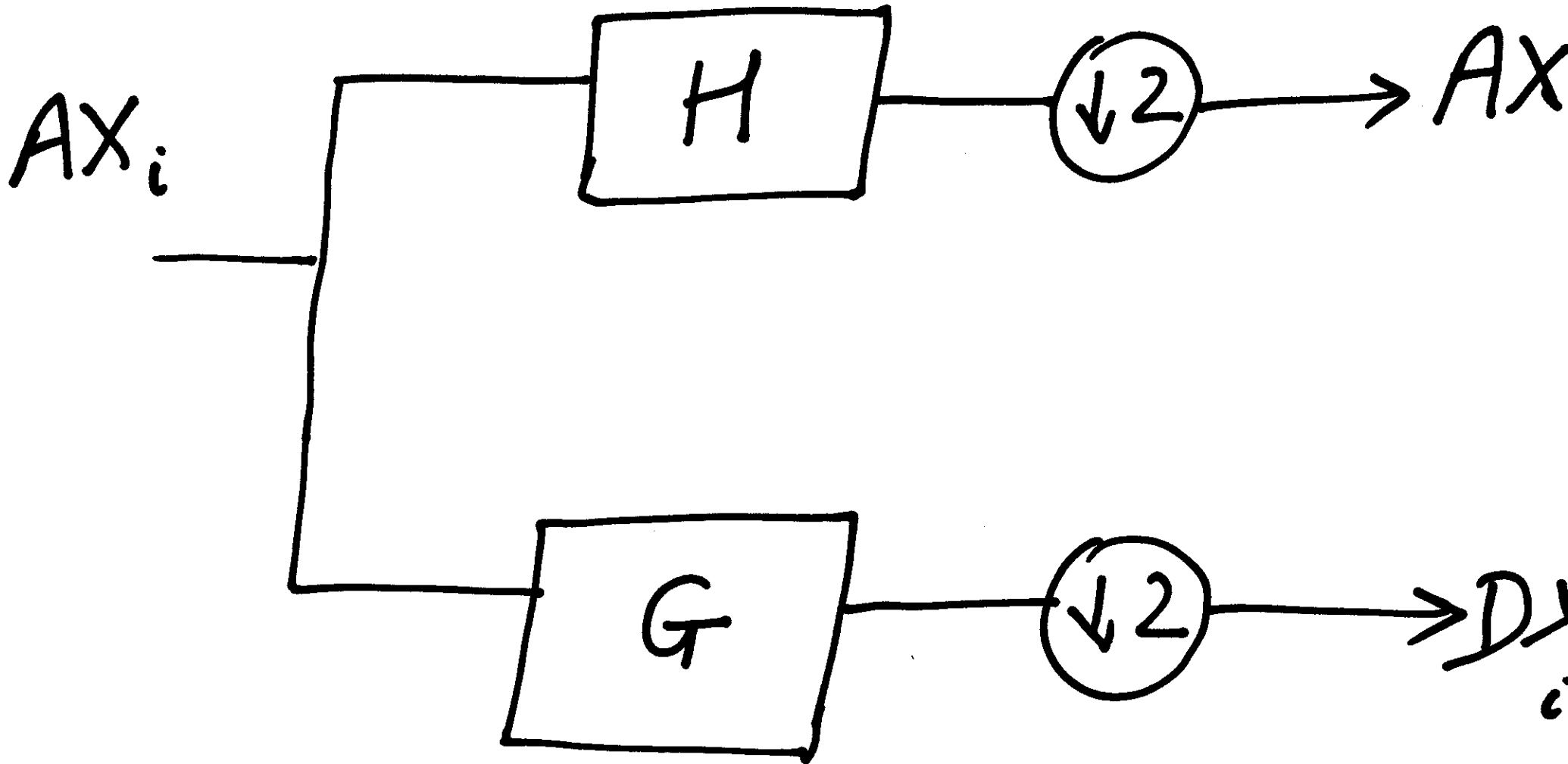
reconstruction

$N \times M$

(2) \tilde{X} is not updated

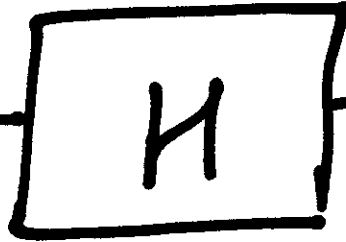
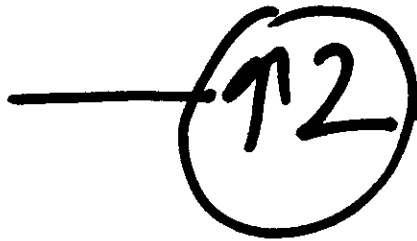
Recompute the whole
matrix again

Split Operation

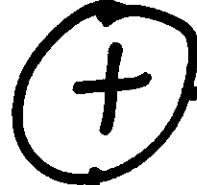


Merge Operation

AX_{i+1}

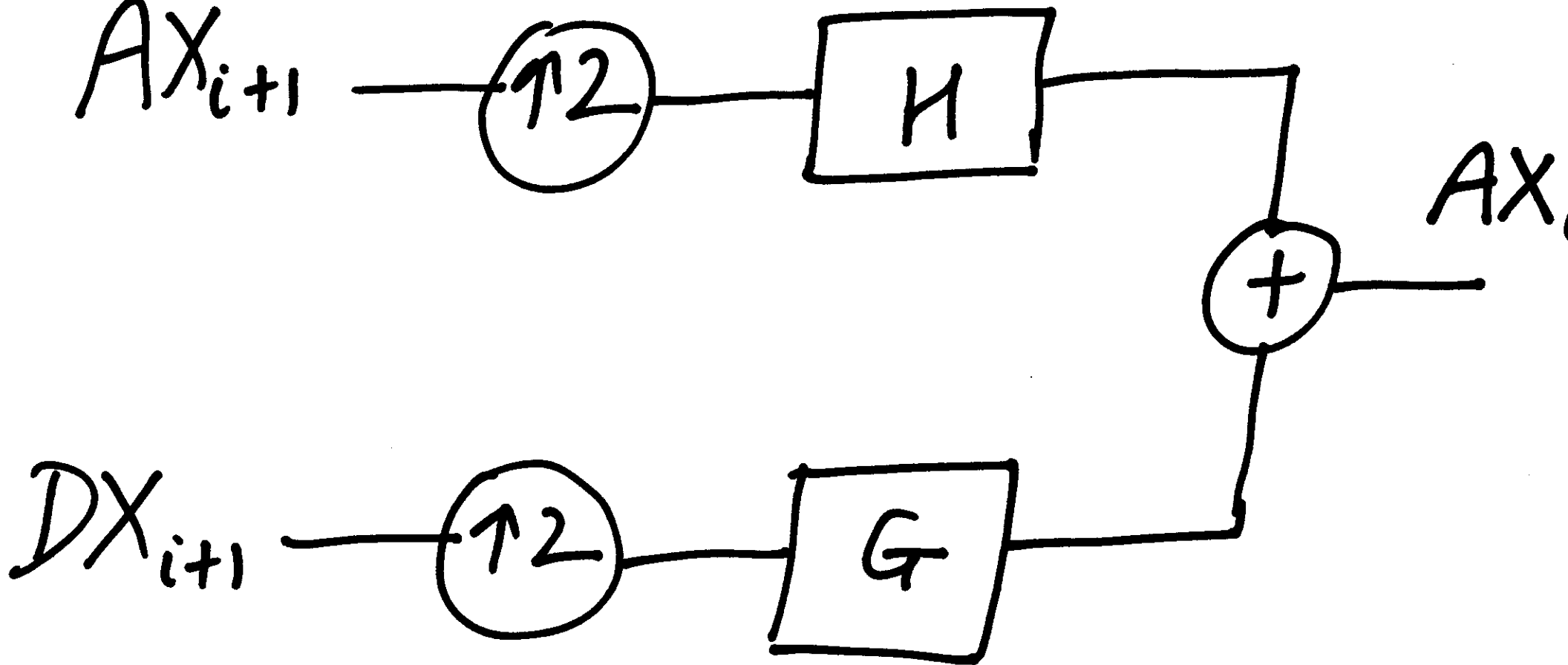
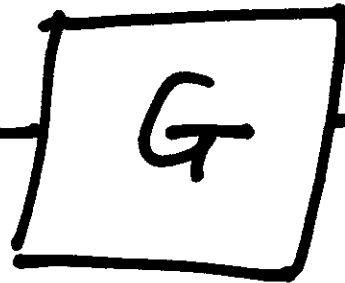
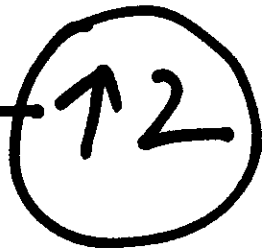


AX_{i+1}



AX_{i+1}

DX_{i+1}

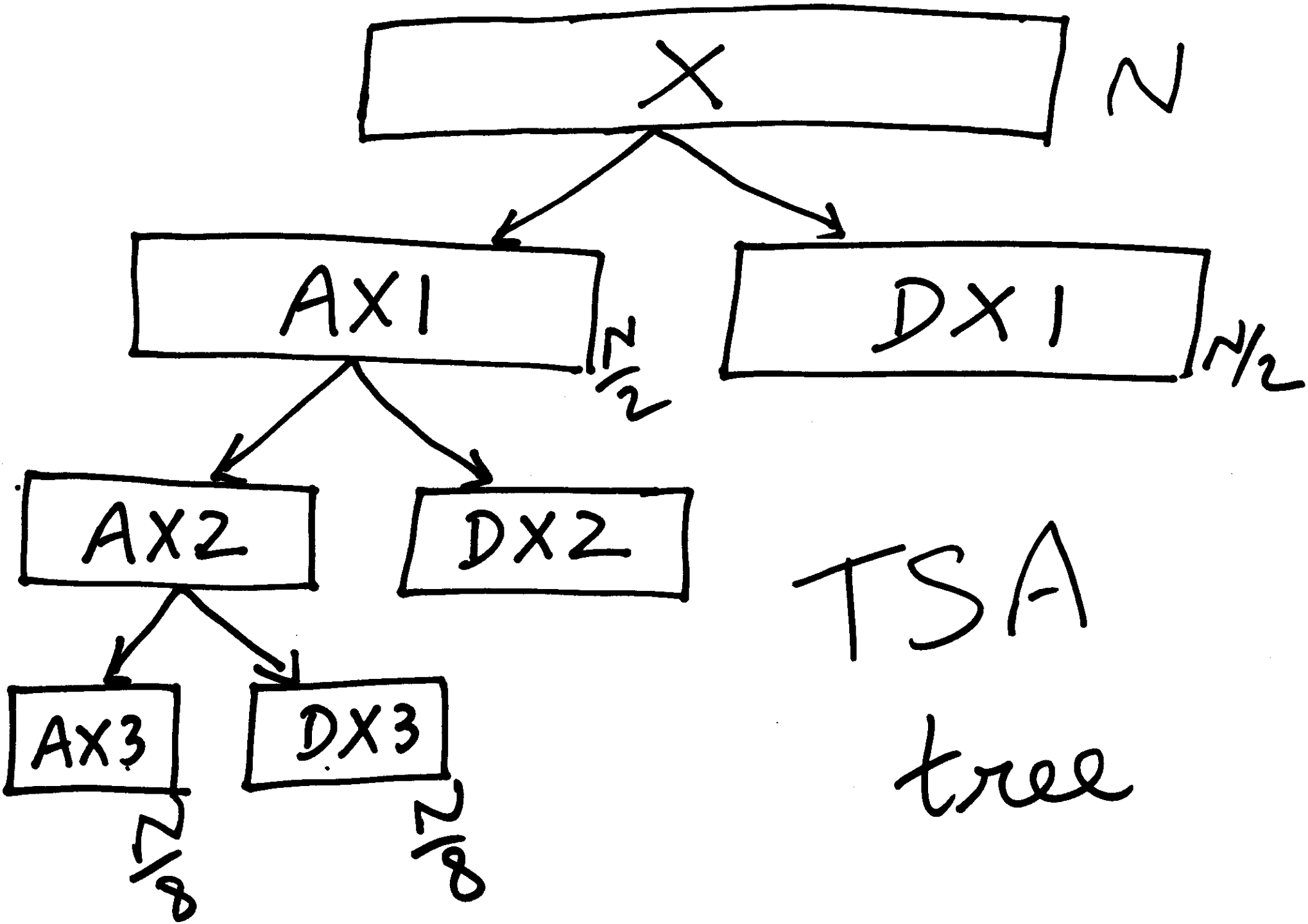


Properties

- (i) Perfect reconstruction
- (ii) Power complementary
- (iii) Size of each node decreases

Assumptions

- (i) Split and merge operations incur negligible cost
- (ii) Cost due to disk I/O operation



TSA
tree

Optimal TSA tree

Store only the leaf
nodes

(1) Node Dropping

Exploit the

Orthogonality

property

$$\|X - \hat{X}\|^2 = \sum_{\text{node} \in S} \|\text{node}\|^2$$

Use a greedy algorithm

$$\frac{\text{norm}^2(\text{node})}{\text{size}(\text{node})}$$

(2) No-efficient Dropping

- Store co-efficients

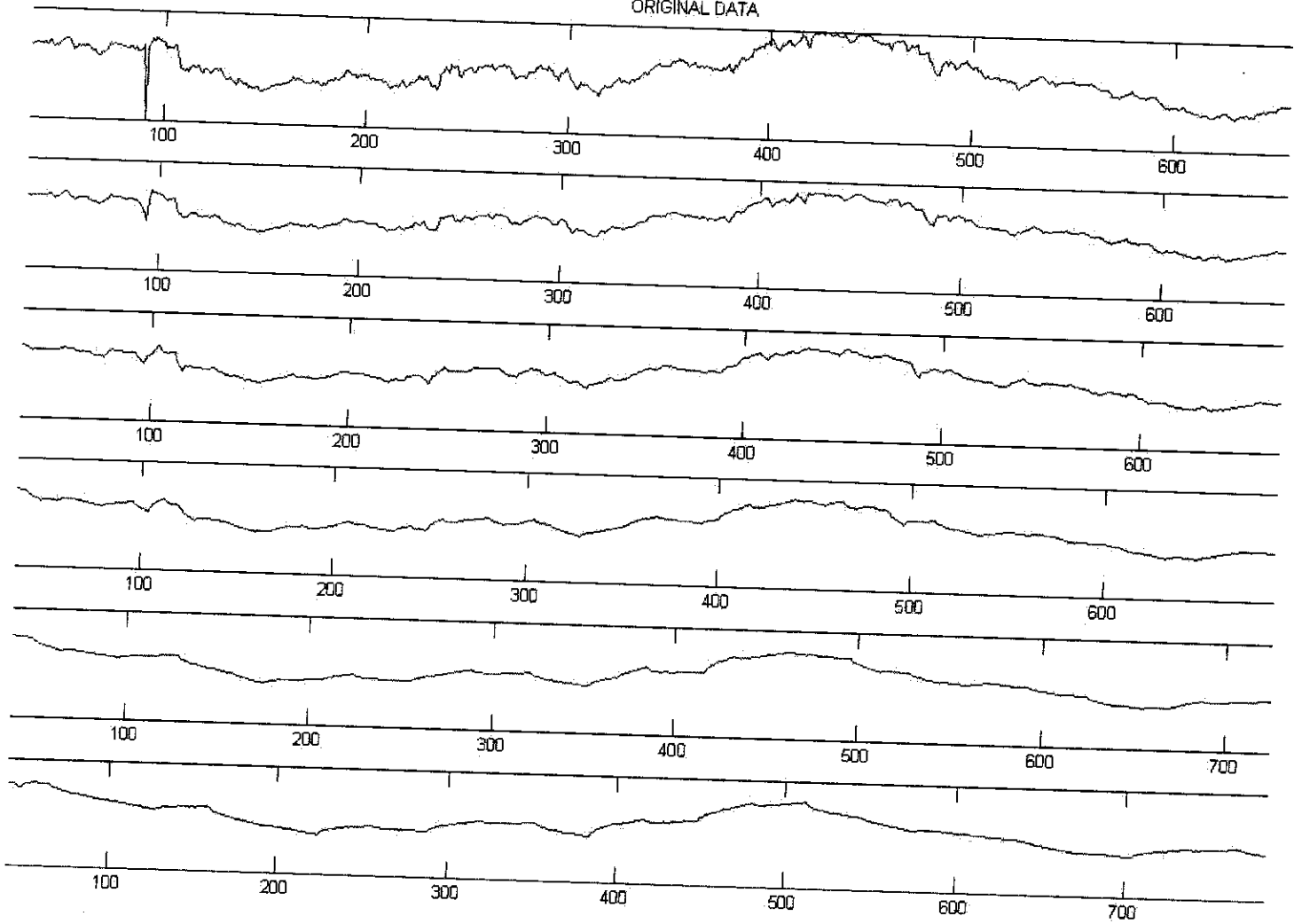
- Store indexes

Application of Wavelets in Data Mining

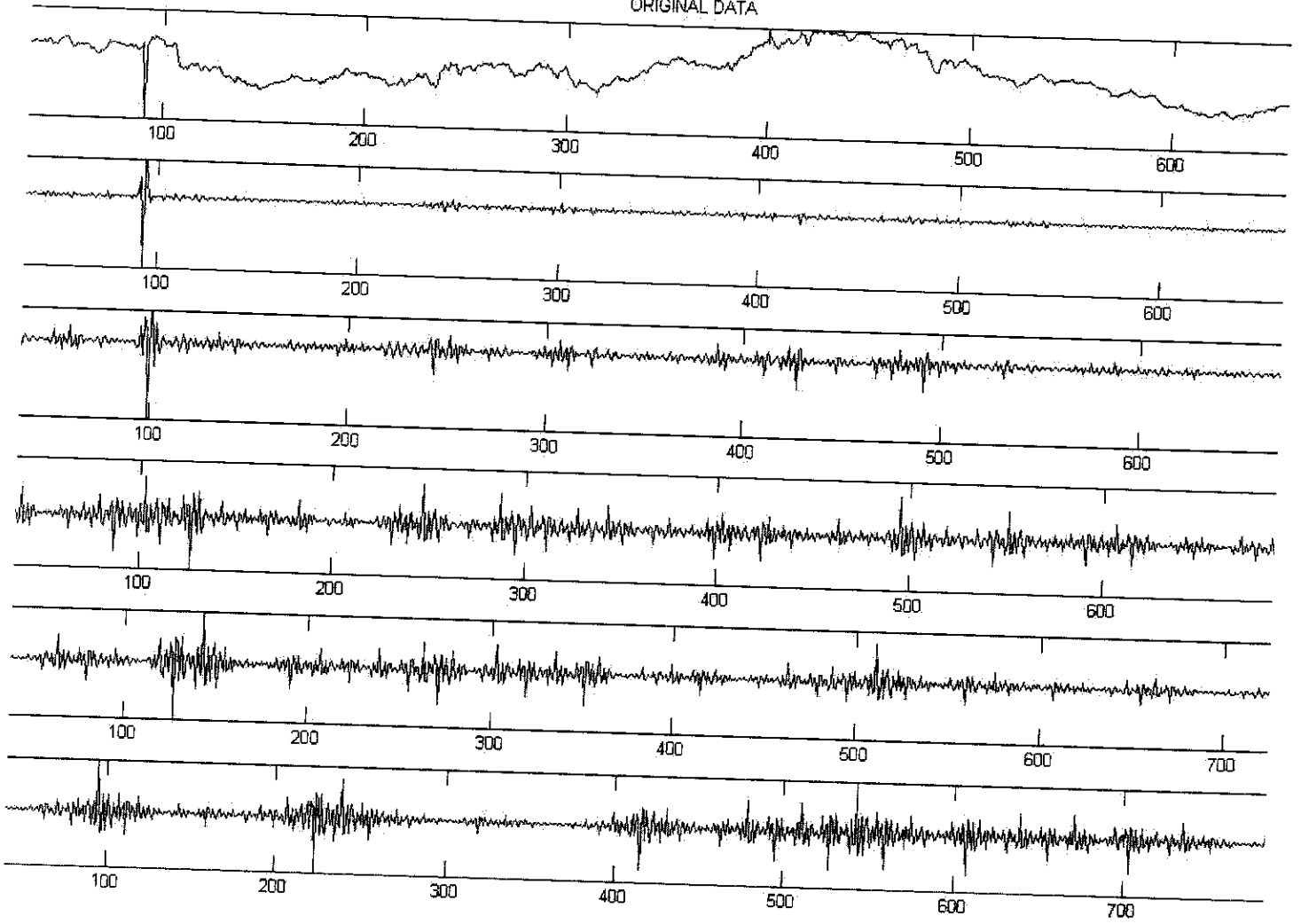
Instructor : Prof V. M. Gadre

Kunal Shah (09307001)
Arka Chowdhury (09307402)

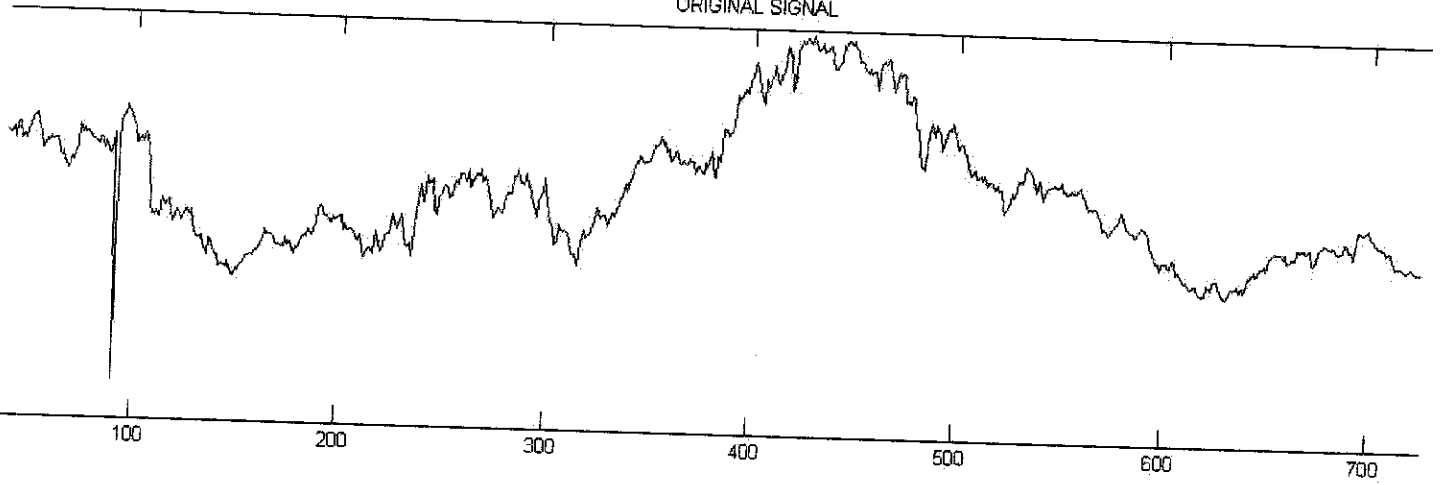
ORIGINAL DATA



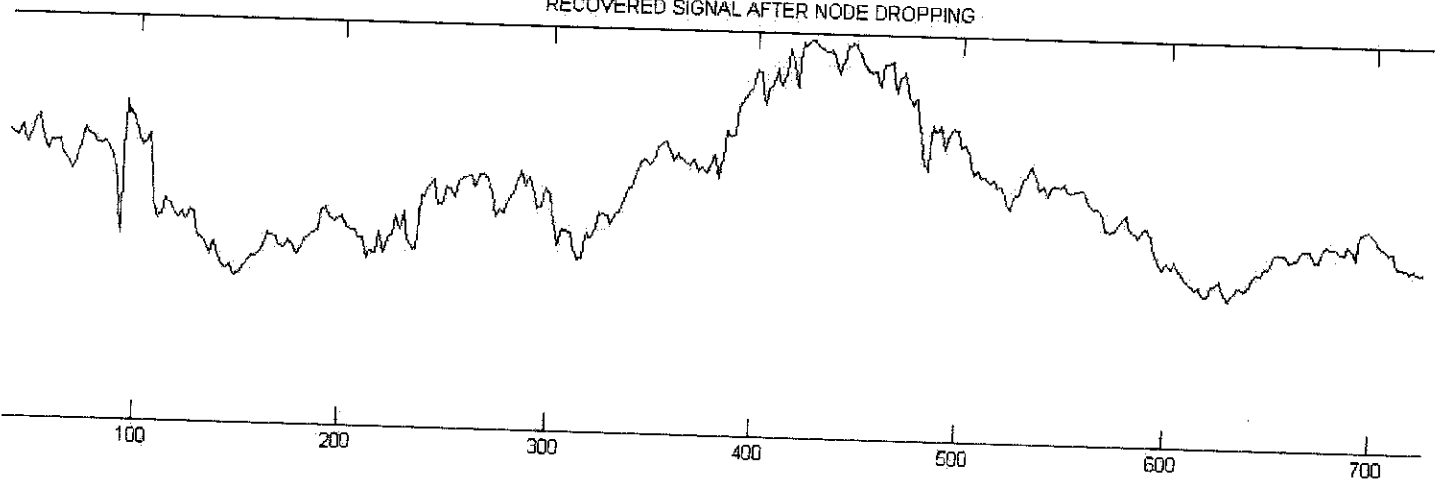
ORIGINAL DATA



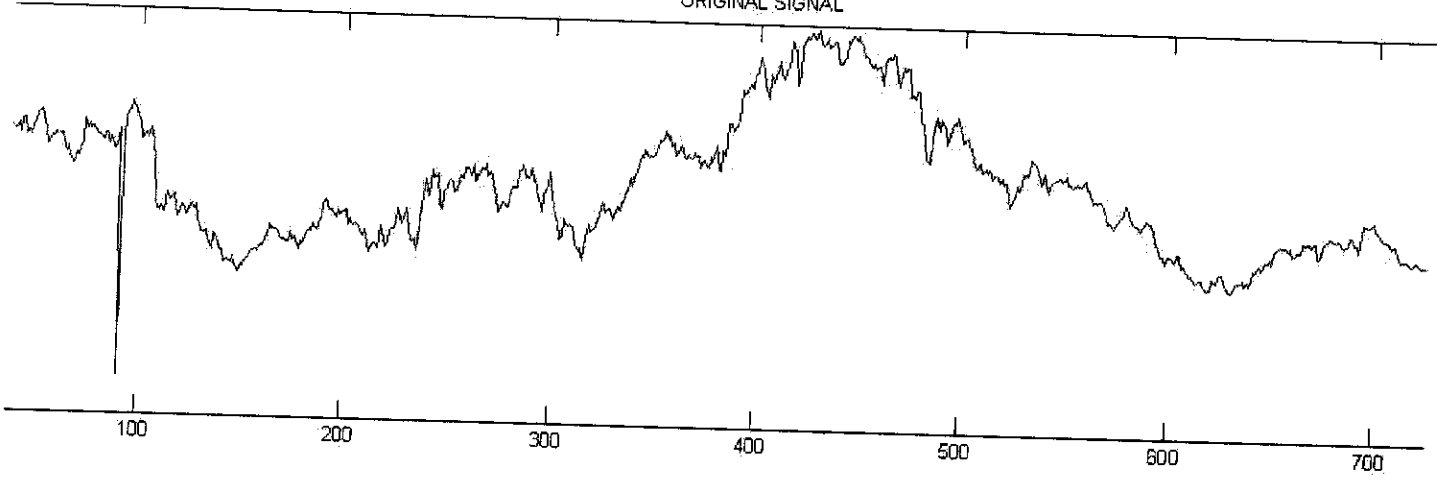
ORIGINAL SIGNAL



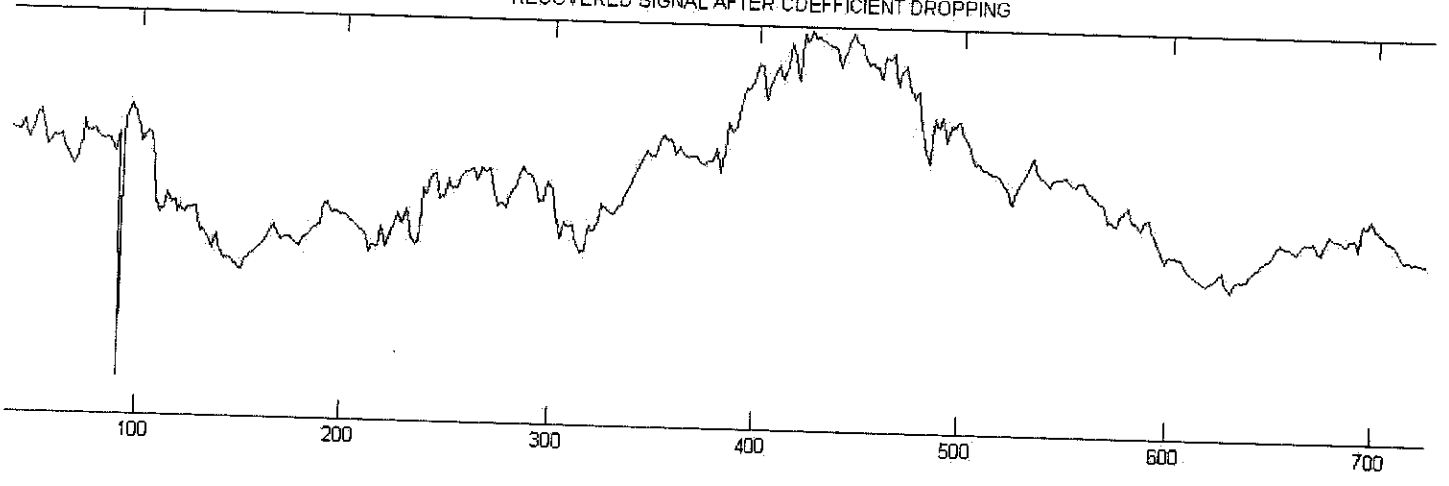
RECOVERED SIGNAL AFTER NODE DROPPING



ORIGINAL SIGNAL



RECOVERED SIGNAL AFTER CDEFFICIENT DROPPING



Reference

C. Shahabi, X.Tian, W. Zhao. TSA tree: A Wavelet-based Approach to Improve the Efficiency of Multi-Level Surprise and Trend Queries on Time-Series Data. In Statistical and Scientific Database Management, pages 55 – 68, 2000.

Reference

Stock prices of SBI taken from Yahoo stock.
Hyperlink:

[http://finance.yahoo.com/q/hp?s=SBIN.NS&a=09 &b=27&c=2006&d=09&e=26&f=2009&g=d](http://finance.yahoo.com/q/hp?s=SBIN.NS&a=09&b=27&c=2006&d=09&e=26&f=2009&g=d)

FACE RECOGNITION
THROUGH WAVE-PACKET
ANALYSIS

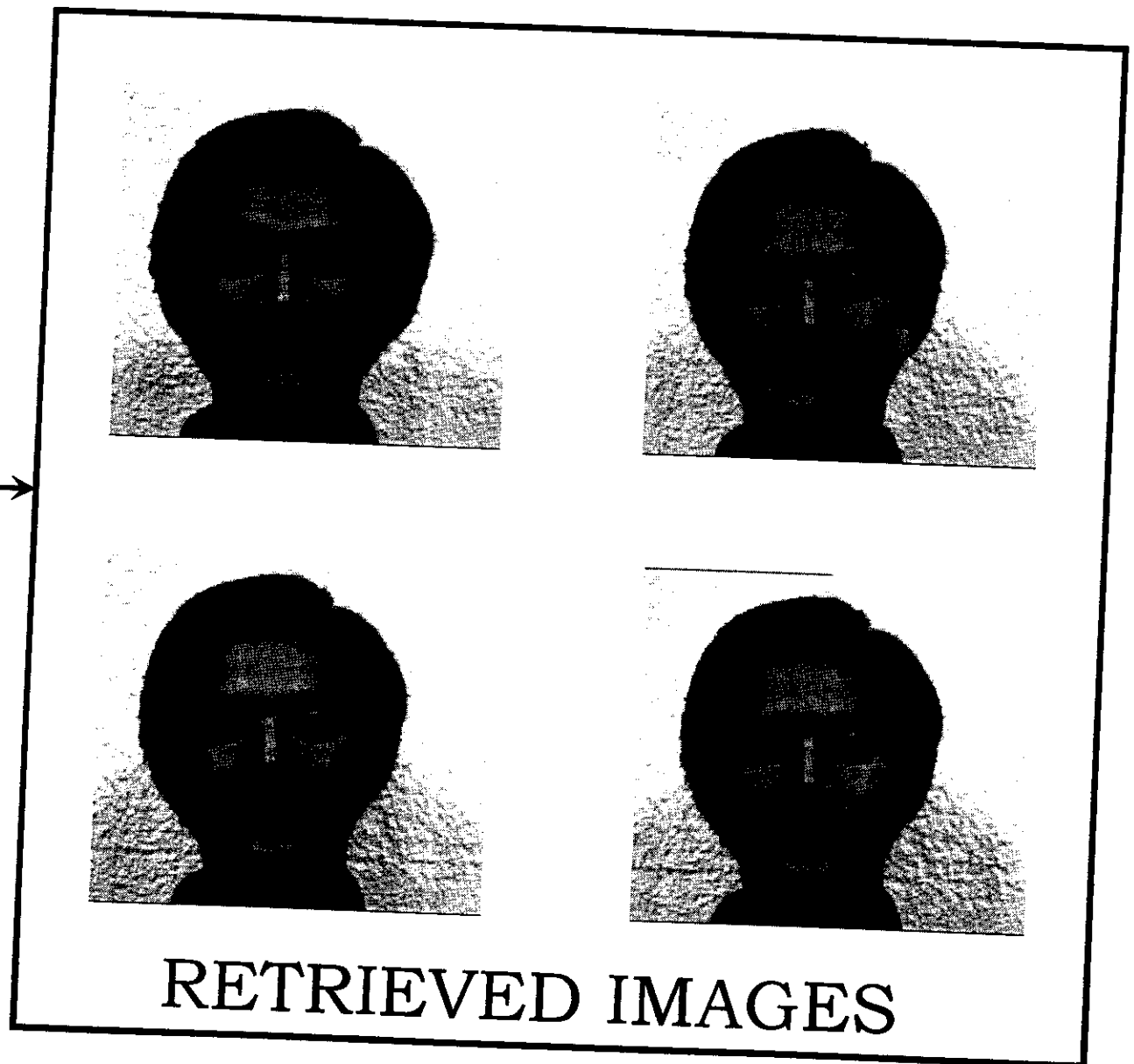
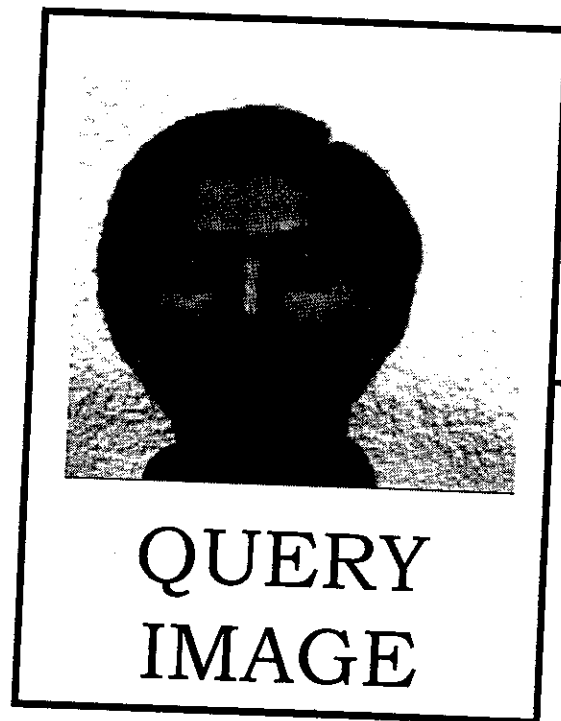
Instructor: Prof. V. M. Gadre

Presented by: Shah Ronak

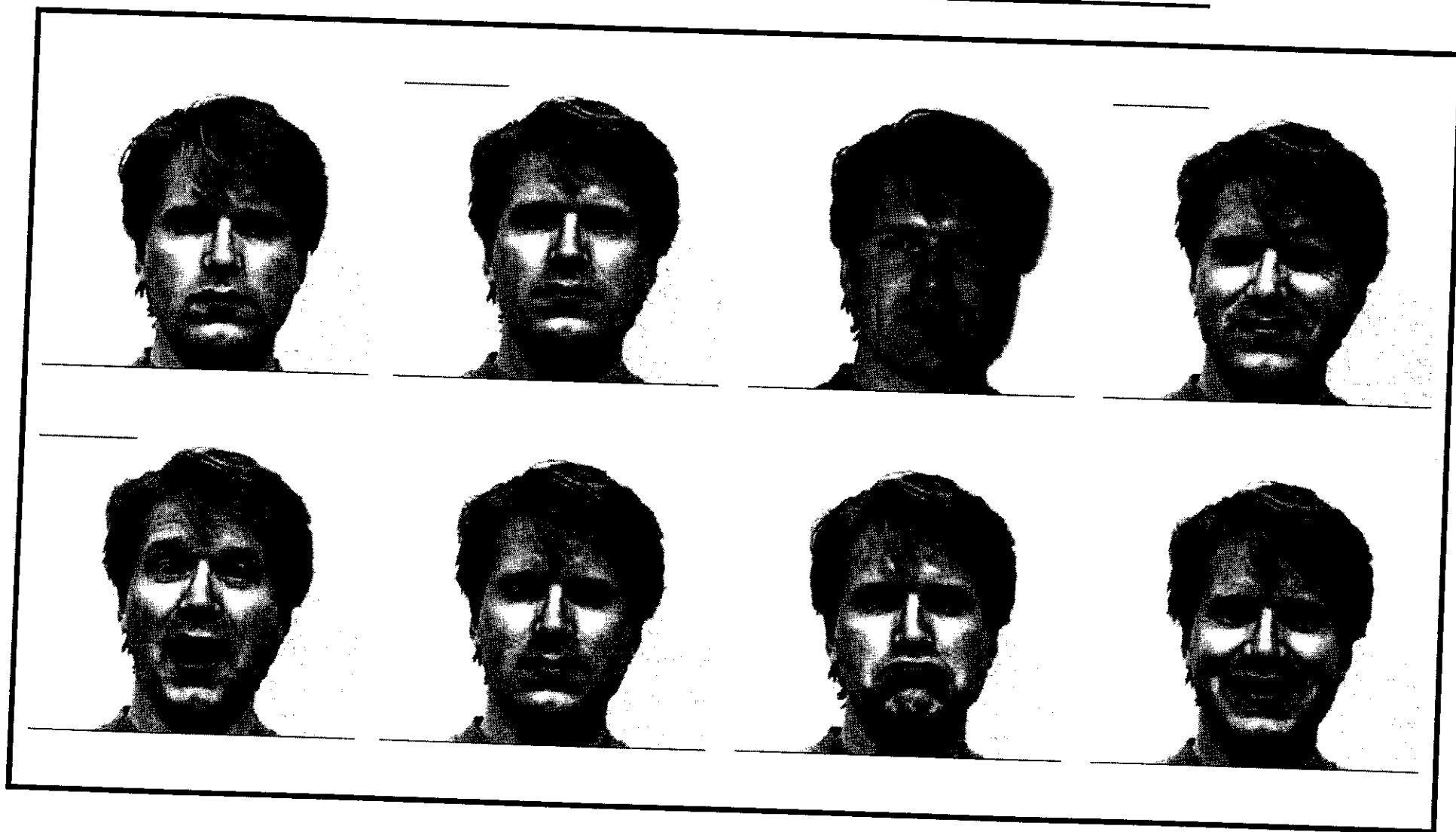
EXPERIMENTAL RESULTS

Exp	Number of Images used in Learning/class	Total Images used in learning	Total number of query images	Number of images matched to the native class	Accuracy ($\pm 1.25\%$)
1	4	40	80	66	82.5%
2	6	60	80	64	80.0%
3	8	80	80	64	80.0%

TYPICAL ARCHIEVAL RESULT (CBIR INTERFACE)



TYPICAL FACE IMAGES FOR ONE SUBJECT
FROM YALE** FACE DATABASE



** can be downloaded from: <http://cvc.yale.edu/projects/yalefaces/yalefaces.html> For non-commercial use only

DISTANCE METRIC

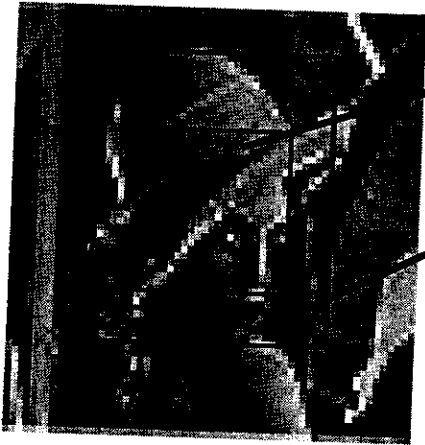
- Why not Euclidean?
- Metric based on Bhattacharyya Distance

$$D(V_k, V_l) = \sum_{f=1}^{17} D_f(V_k, V_l)$$

$$D_f(V_k, V_l) = \frac{1}{4} \frac{(\mu_{fk} - \mu_{fl})^2}{(\sigma_{fk}^2 + \sigma_{fl}^2)} + \frac{1}{2} \ln \left[\frac{\frac{1}{2} (\sigma_{fk}^2 + \sigma_{fl}^2)}{\sqrt{\sigma_{fk}^2 \sigma_{fl}^2}} \right]$$

FEATURE VECTOR EXTRACTION

Approximation Subspace (4 features)



Mean (μ_1) & Variance (σ_1^2)

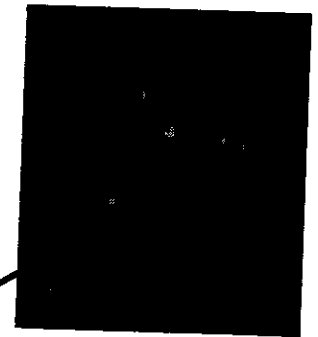
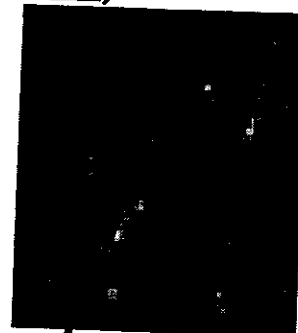
Mean (μ_2) & Variance (σ_2^2)

19 / Image!!

Detail Subspaces (15 features)

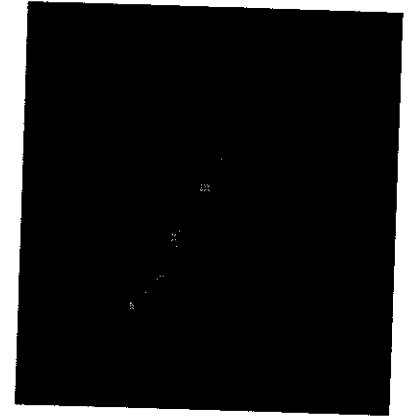
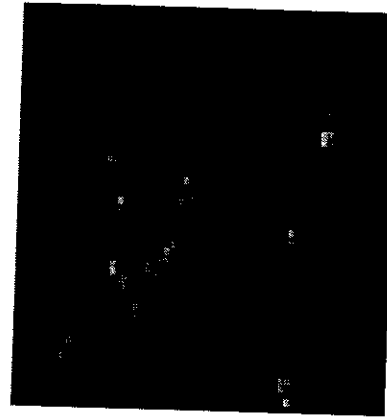
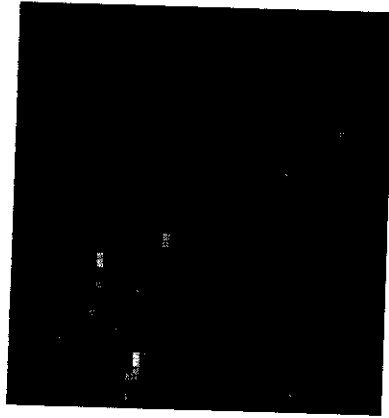
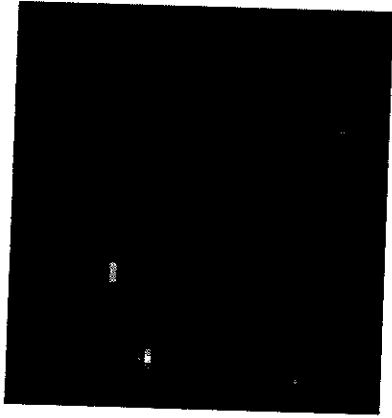


...

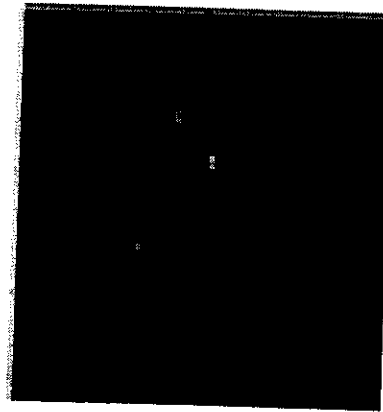
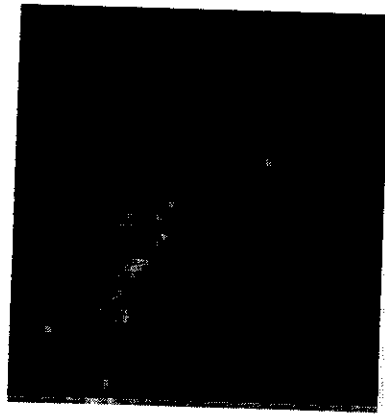


Mean (μ_j) 'zero' & hence Variance (σ_j^2) only

SUBSPACES OBTAINED AT SECOND
LEVEL OF DECOMPOSITION (contd..)



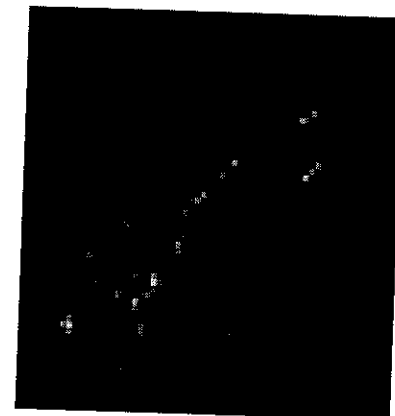
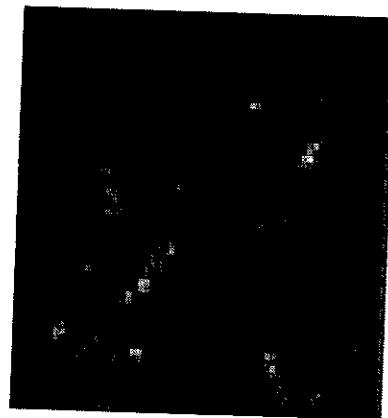
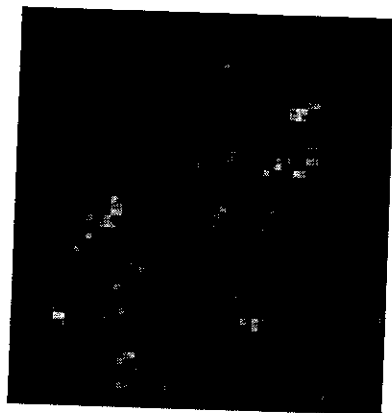
DETAIL SUBSPACES



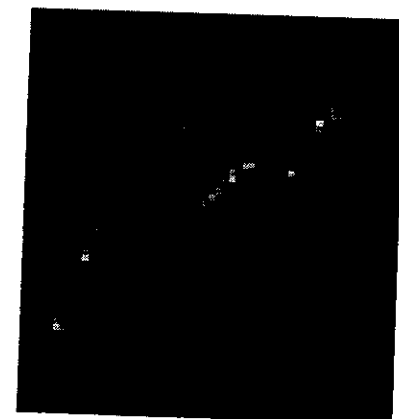
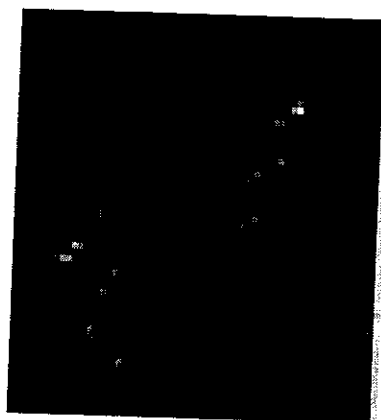
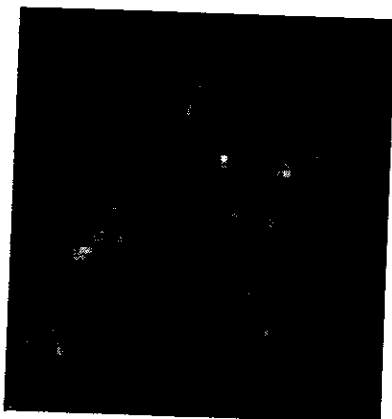
SUBSPACES OBTAINED AT SECOND LEVEL OF DECOMPOSITION



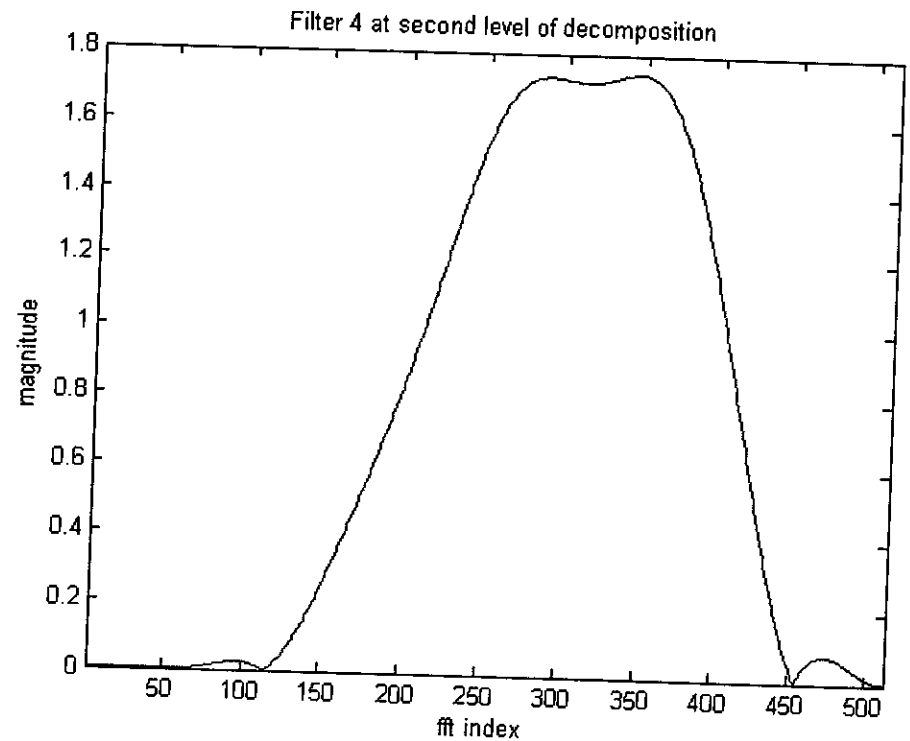
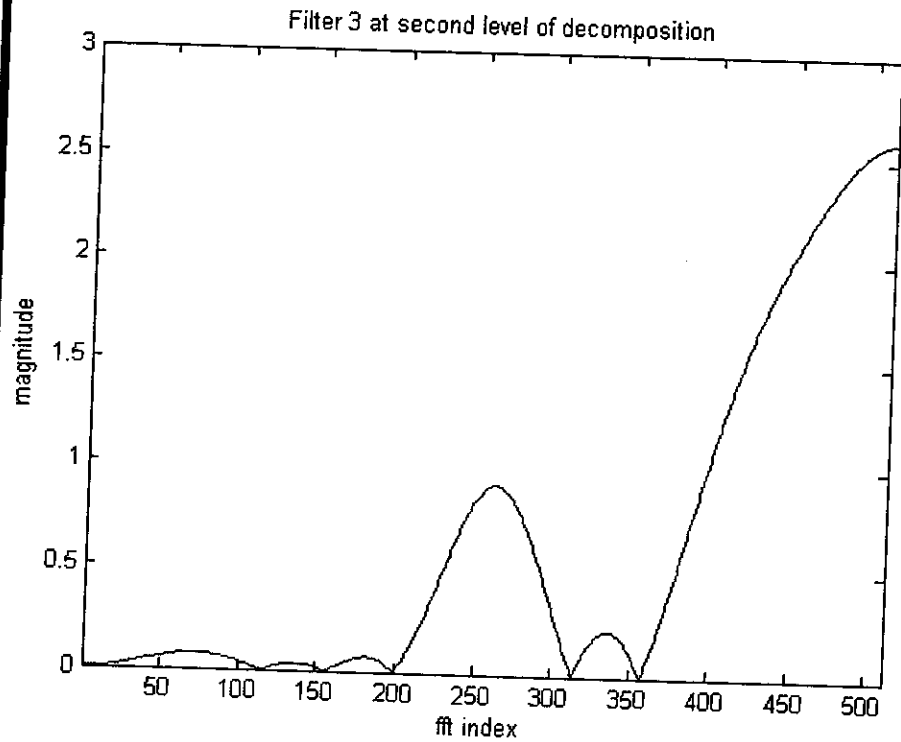
APPROX



DETAIL SUBSPACES



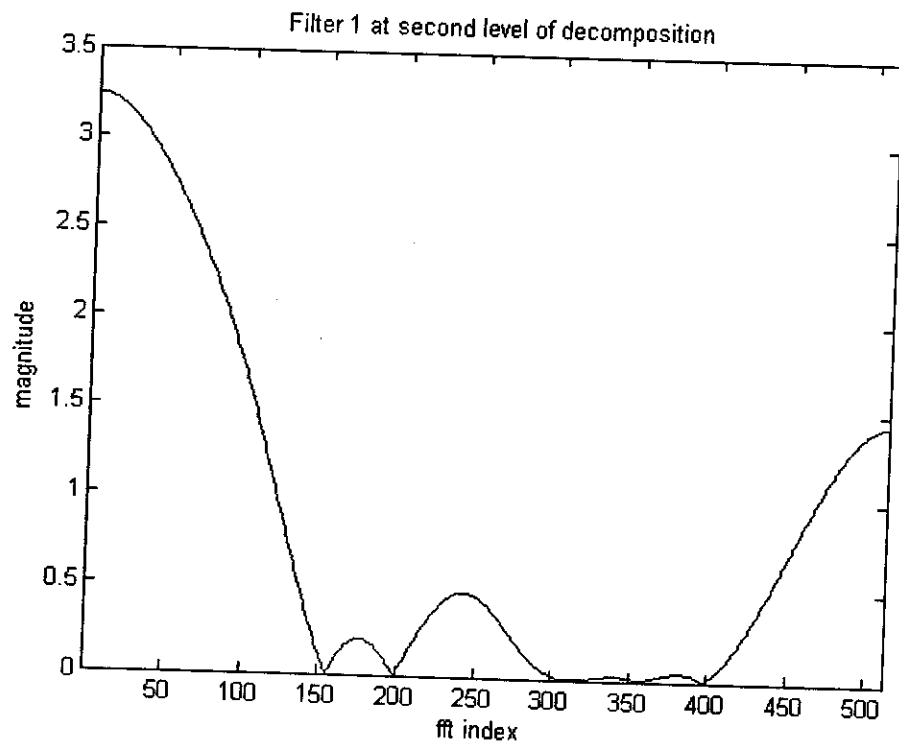
MAGNITUDE RESPONSES AT SECOND LEVEL OF DECOMPOSITION (contd..)



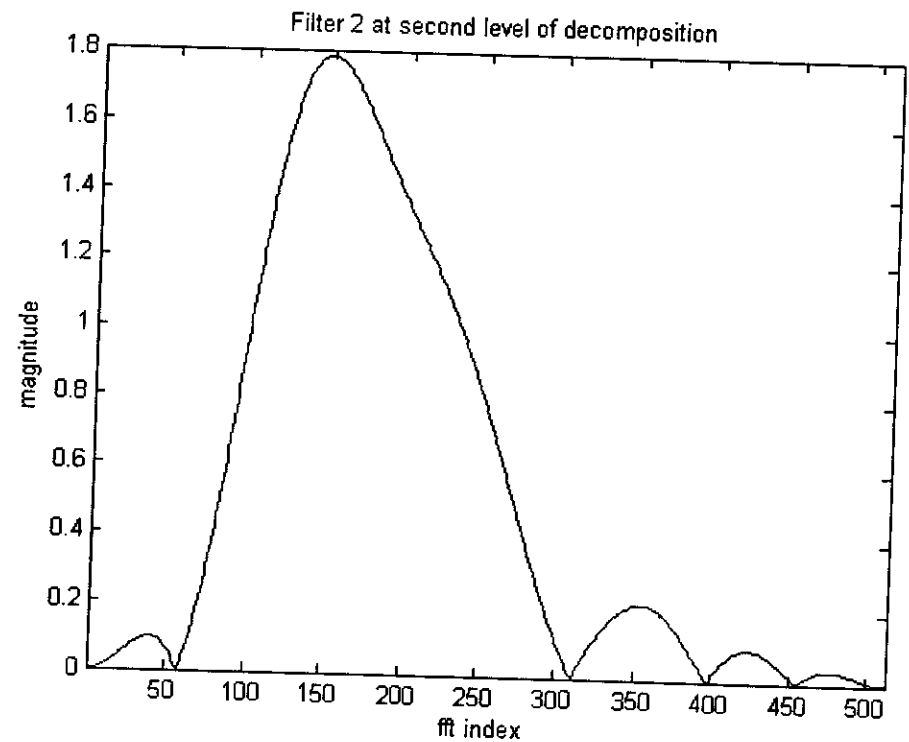
HPF Magnitude Response

BPF Magnitude Response

MAGNITUDE RESPONSES OF FILTERS AT SECOND LEVEL OF DECOMPOSITION

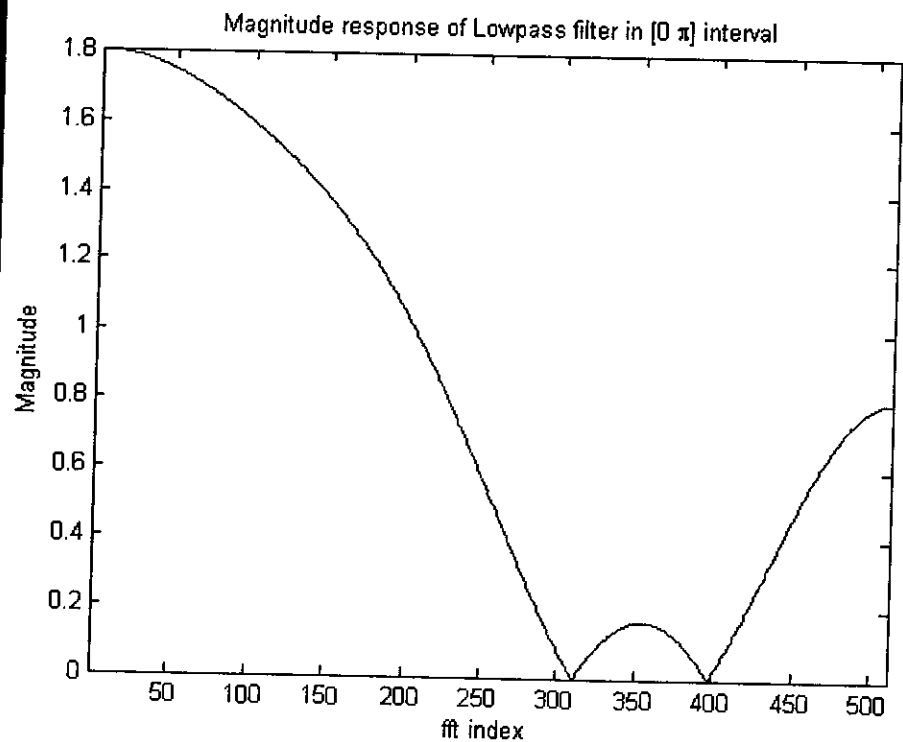


LPF Magnitude Response

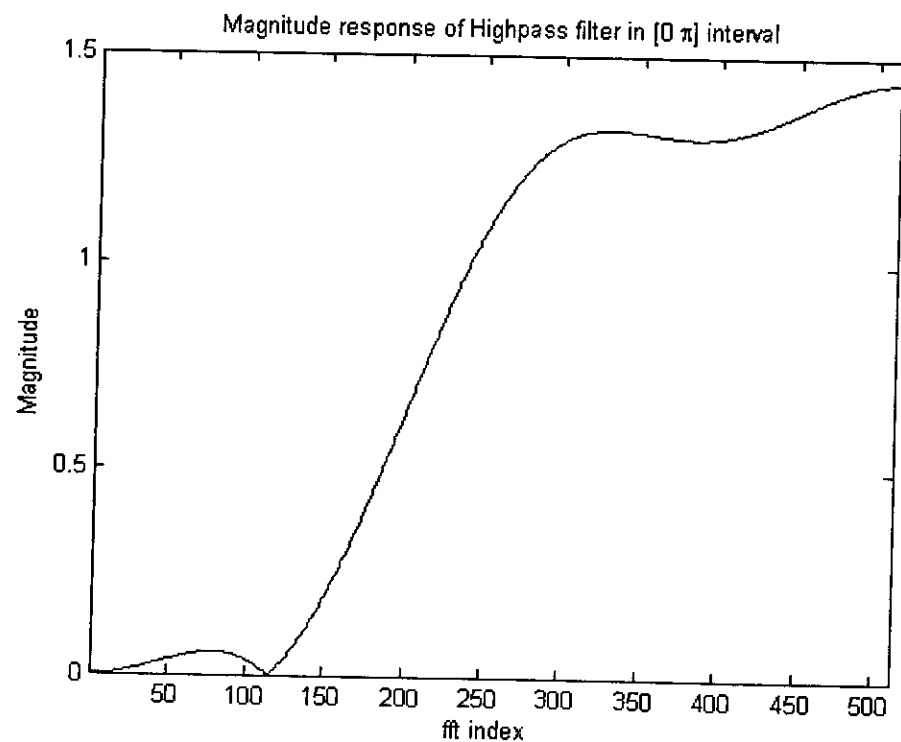


BPF Magnitude Response

MAGNITUDE RESPONSES OF FILTERS

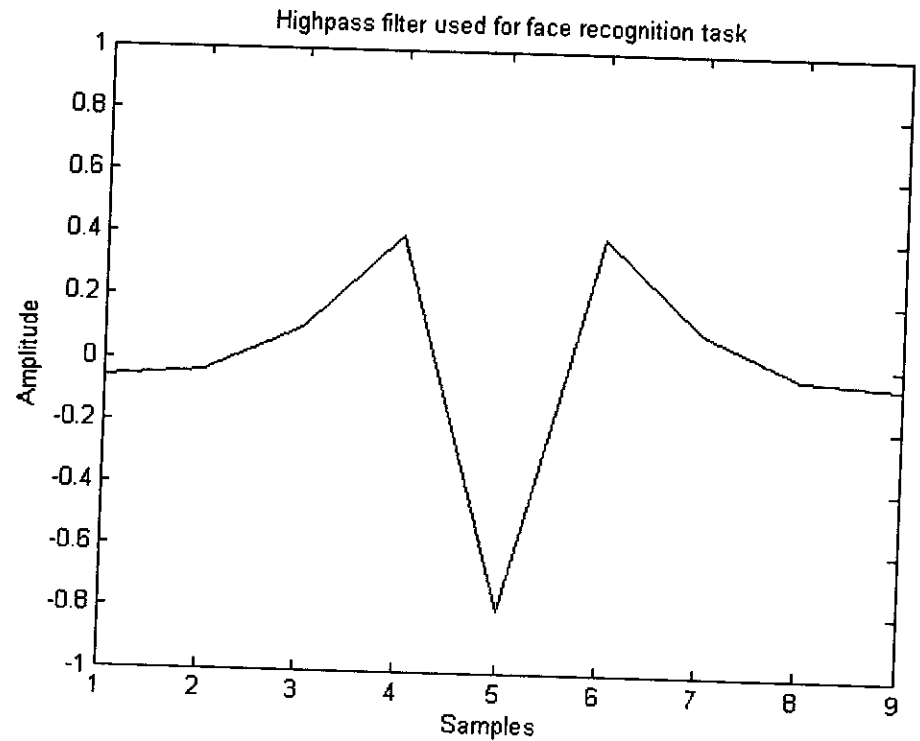
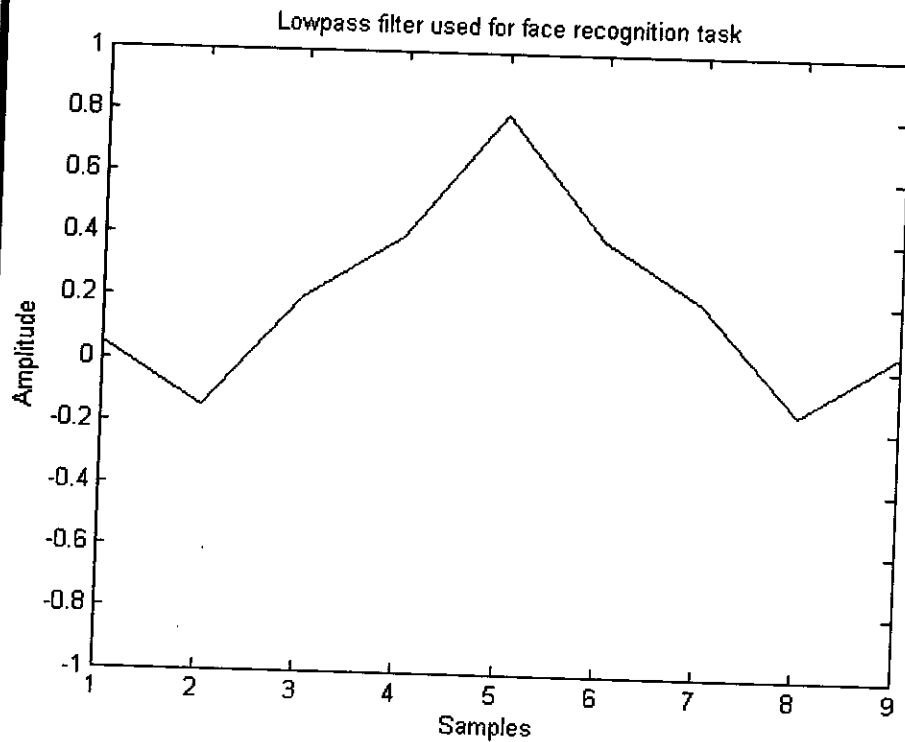


LPF Magnitude Response



HPF Magnitude Response

FILTERS IN ACTION

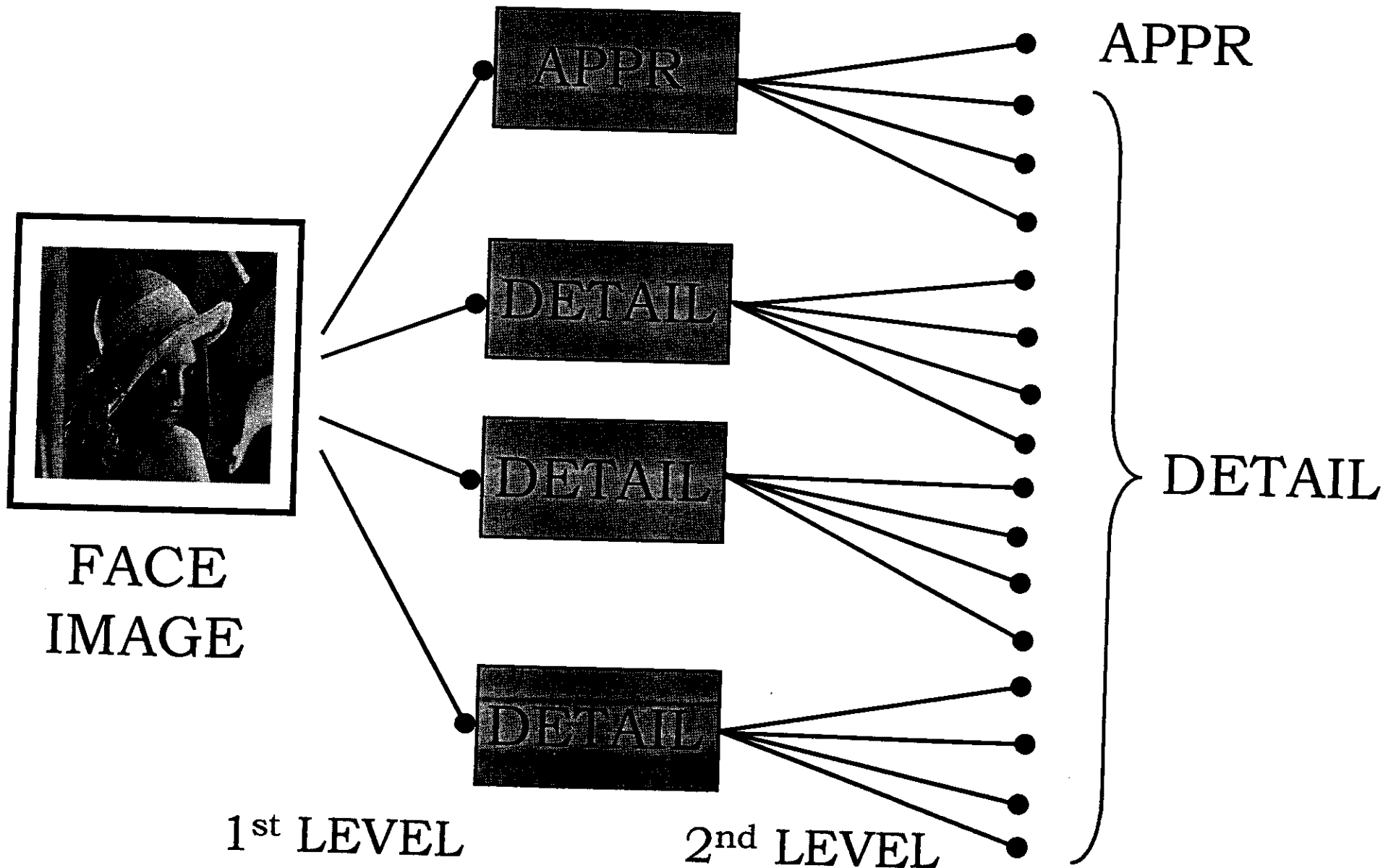


LPF Impulse Response

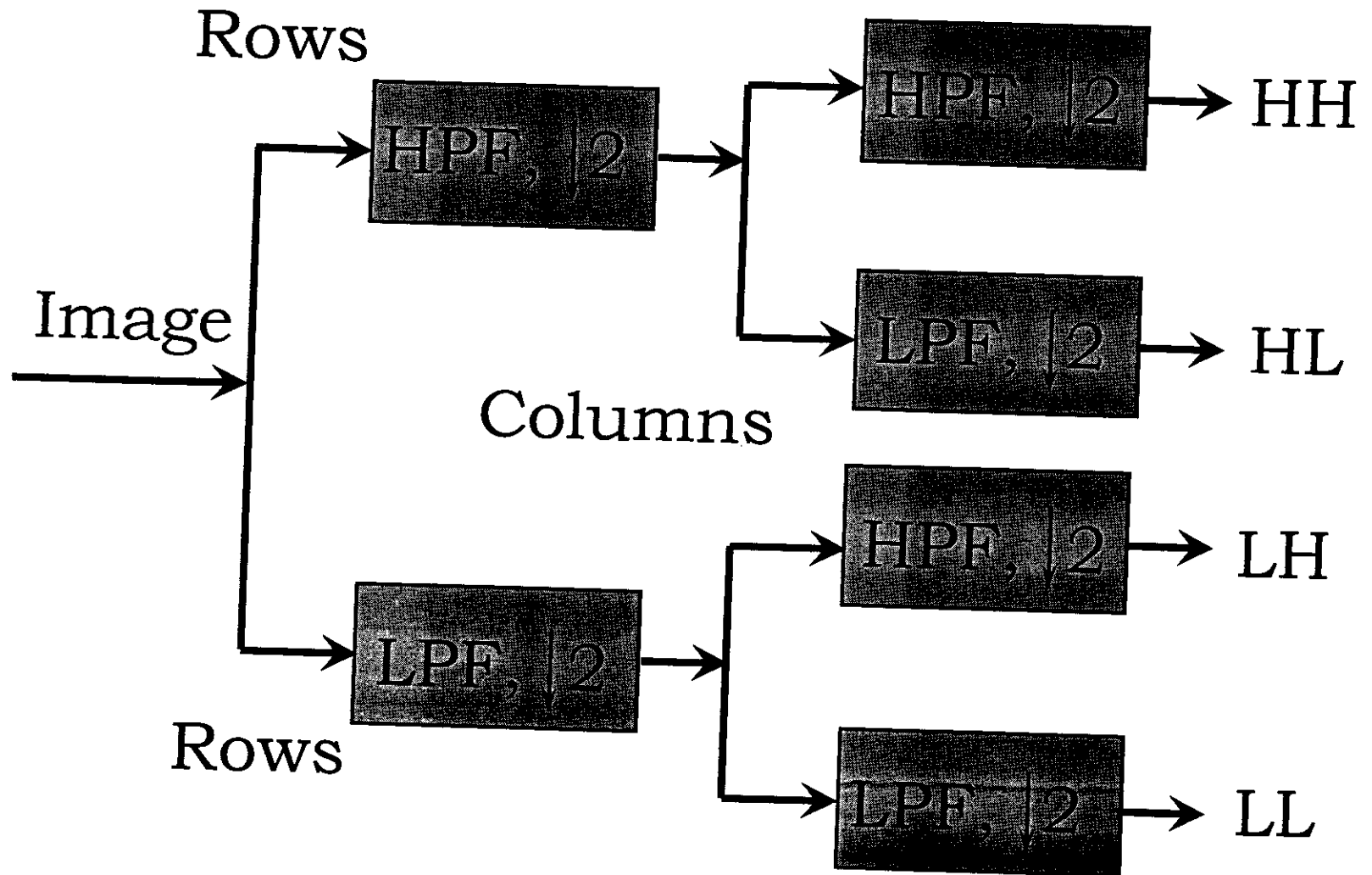
HPF Impulse Response

Filter	Impulse Responses								
LPF	0.05	-0.15	0.20	0.40	0.80	0.40	0.20	-0.15	0.05
HPF	-0.06	-0.04	0.10	0.40	-0.80	0.40	0.10	-0.04	-0.06

TWO-LEVEL WAVE-PACKET DECOMPOSITION



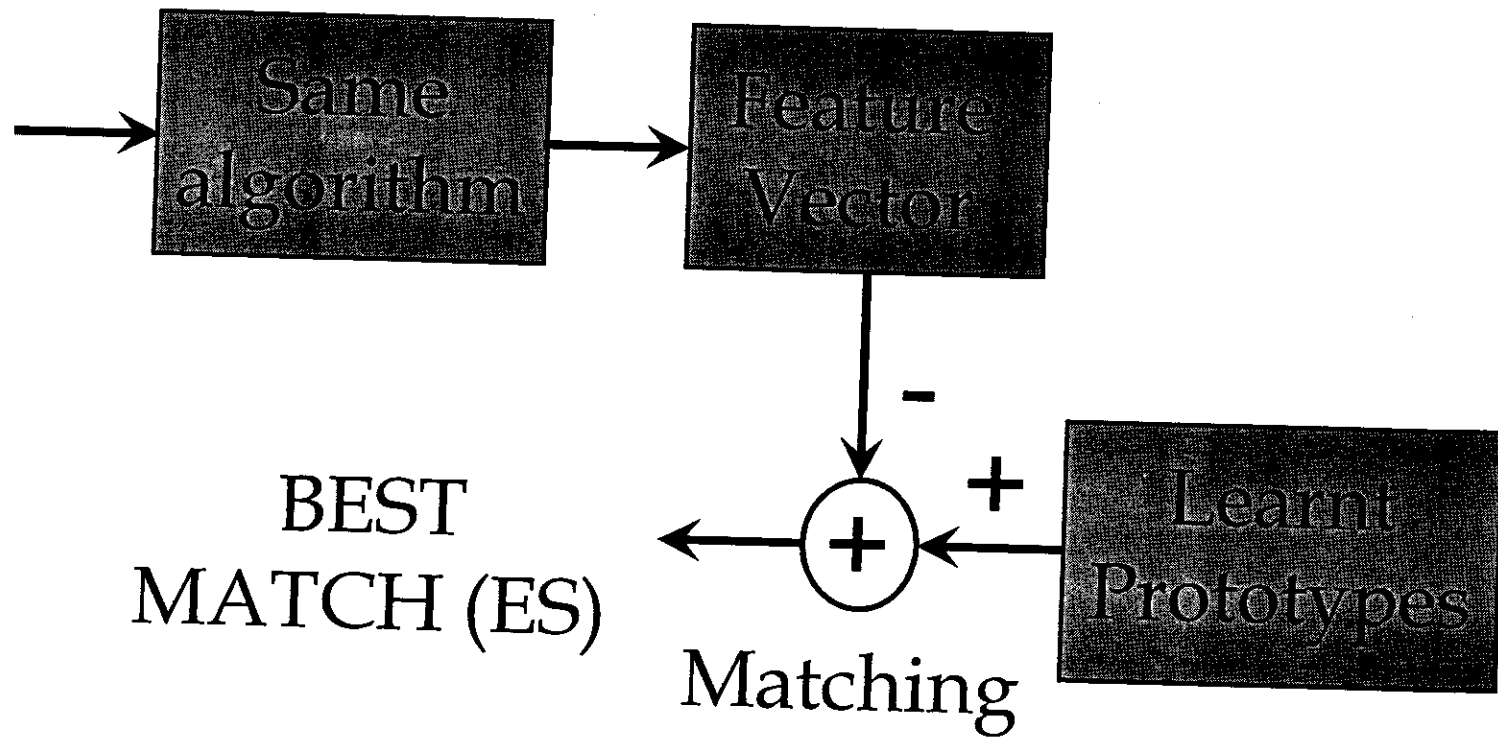
Traditional filter-bank structure For Image



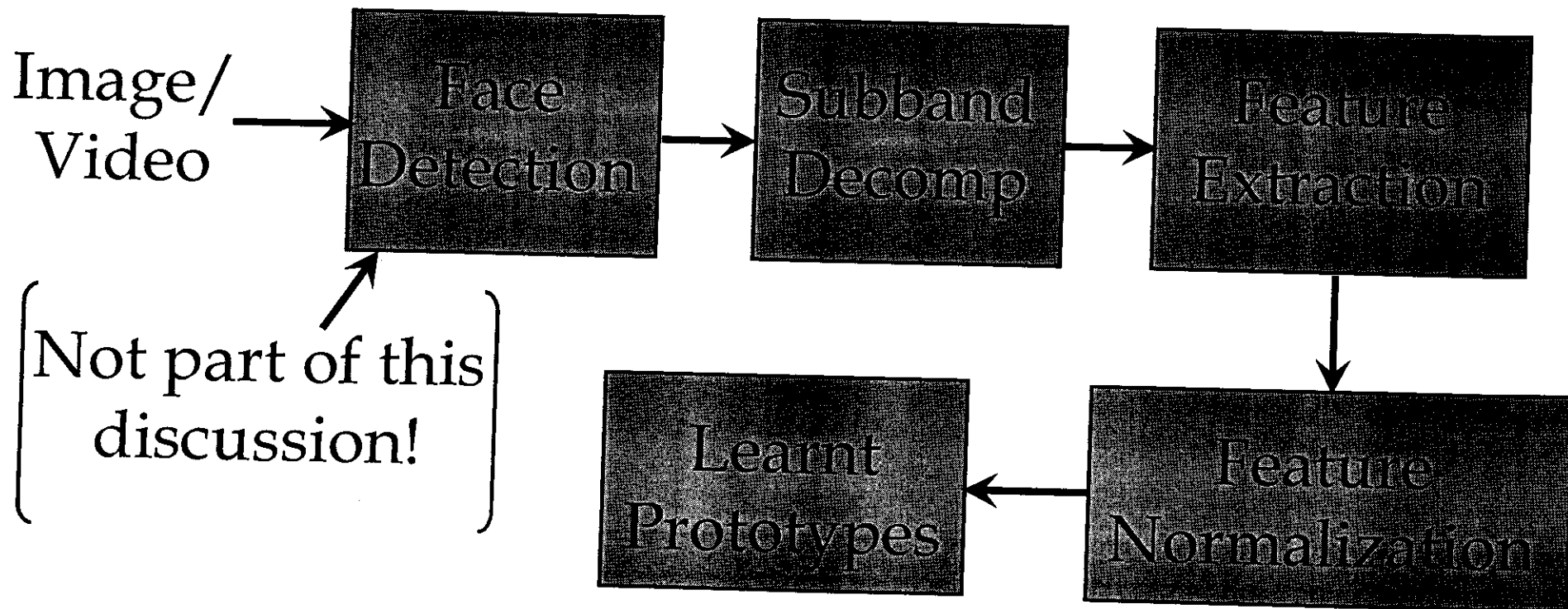
BLOCK DIAGRAM (MATCHING)



Query
Image



BLOCK DIAGRAM (PROTOTYPE LEARNING)



APPROACHES

➤ Geometric approach

➤ Feature based approach

Why Face Recognition? (contd..)

- Automatic character (actor) recognition
- Image and Video database management for efficient archival

Why Face Recognition?

➤ Bio-metric Recognition?

➤ Surveillance

Activity Tracking
& Recognition

Abnormality
Detection

REFERENCES (contd..)

- 3) R. Brunelli, T. Poggio. Face Recognition: Features versus Templates. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 11(6): 1042-1052, 1993.
- 4) Raghuvveer Rao, A. Bopardikar. Wavelet Transforms: Introduction to theory and applications. *Prentice Hall*, 1998.
- 5) W. Zhao, R. Chellappa, P. Phillips, A. Rosenfeld. Face Recognition: A literature survey. *ACM Computing Surveys*, 35 (4): 399-458, 2003.

REFERENCES

- 1) **C. Garcia, G. Zikos, G. Tziritas. A Wavelet based Framework for Face Recognition. *Fifth European conference on Computer Vision*, 84-92, 1998.**

- 2) P. Belhumeur, J. Hespanha, D. Kriegman. Eigenfaces versus Fisherfaces: Recognition using class specific linear projection. *IEEE transactions on Pattern Analysis and Machine Intelligence*, 19(7): 711-720, 1997.