“Intelligent Extraction of a Digital Watermark from a Distorted Image”

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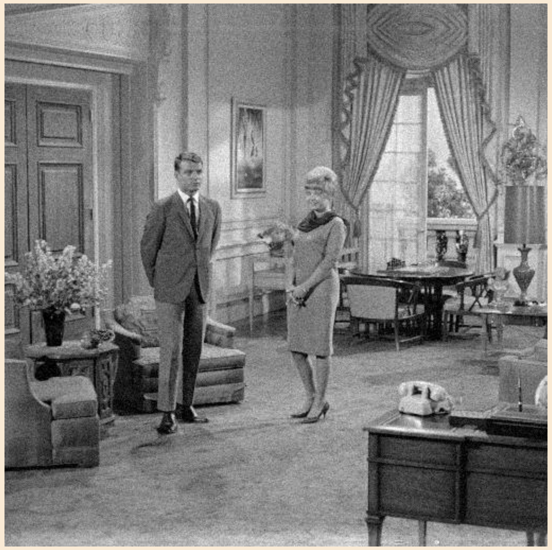
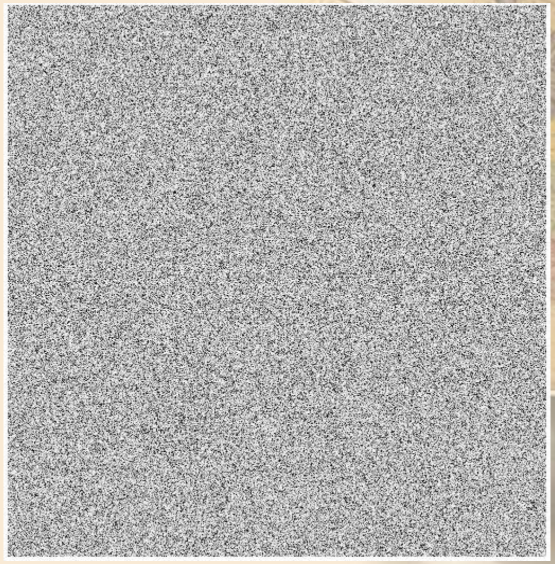
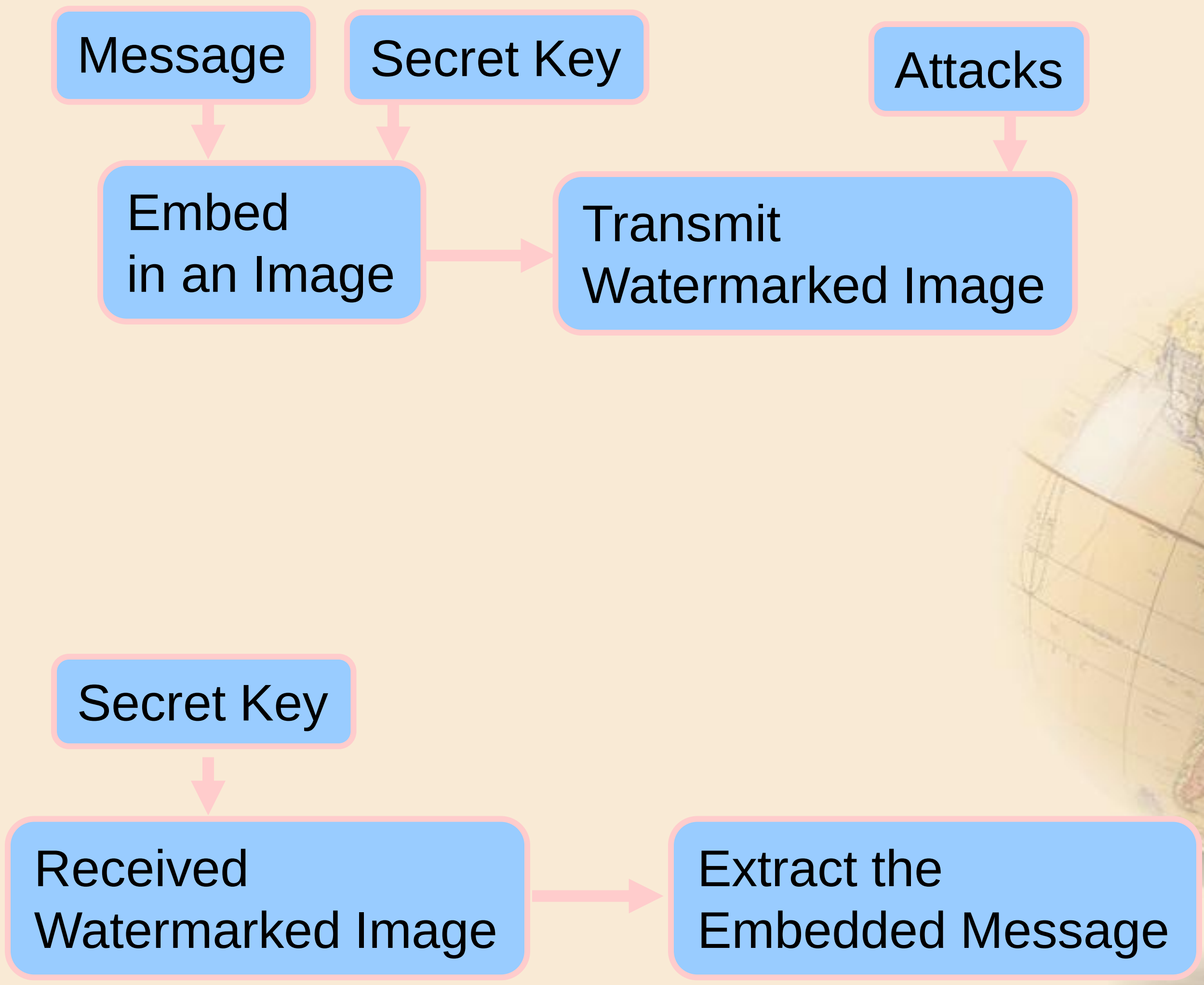
Digital Watermarking

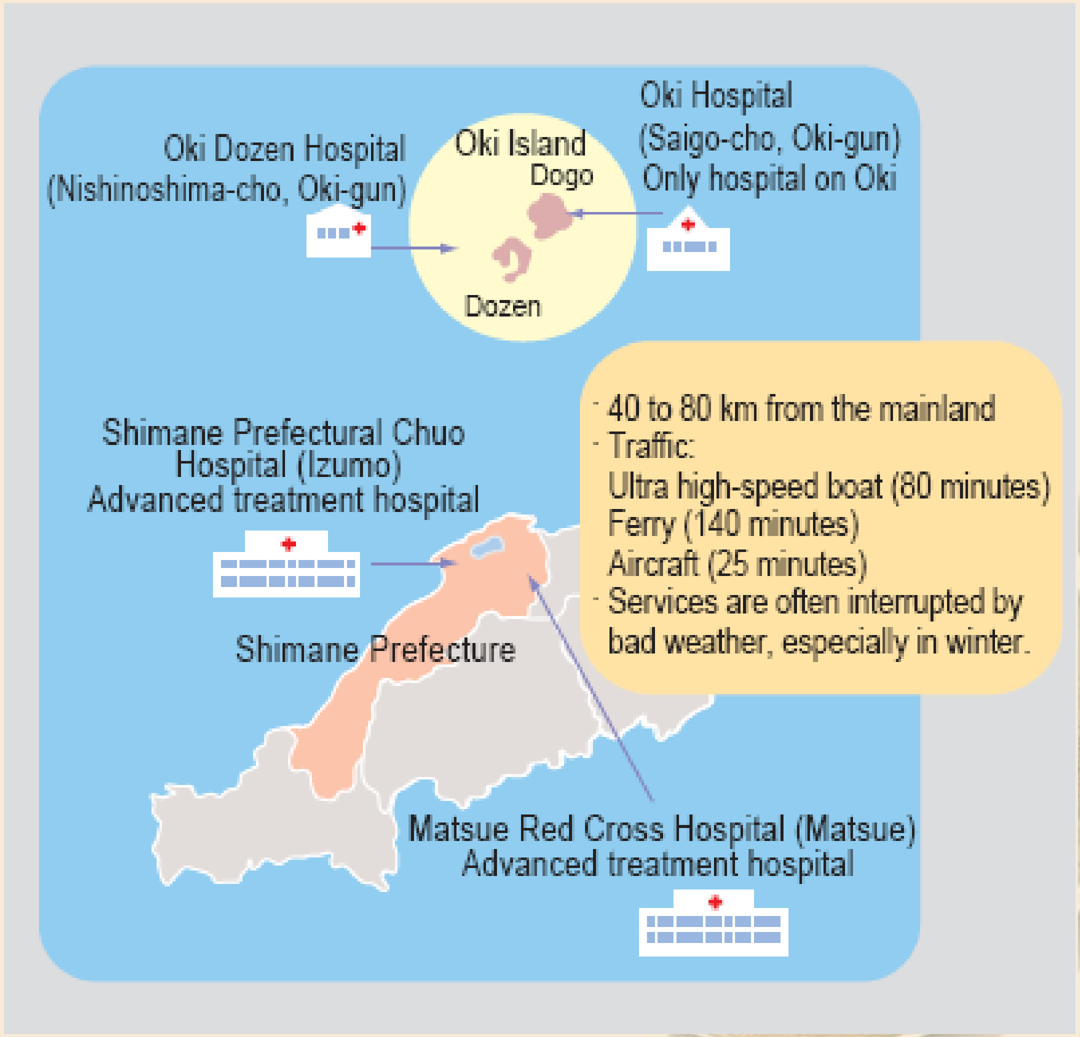



Digital Watermarking (Embedding and Extraction)


Message
Secret Key
Attacks
Embed in an Image
Transmit Watermarked Image
Secret Key
Received Watermarked Image
Extract the Embedded Message

Medical Image Watermarking (Applications)

Remote Medical Treatment System for Isolated Islands[1]


Oki Dozen Hospital (Nishinoshima-cho, Oki-gun)
Oki Island
Dogo
Dozen
Oki Hospital (Saigo-cho, Oki-gun) Only hospital on Oki
Shimane Prefectural Chuo Hospital (Izumo) Advanced treatment hospital
Shimane Prefecture
Matsue Red Cross Hospital (Matsue) Advanced treatment hospital

- 40 to 80 km from the mainland
- Traffic:
  Ultra high-speed boat (80 minutes)
  Ferry (140 minutes)
  Aircraft (25 minutes)
- Services are often interrupted by bad weather, especially in winter.

Patient's radiological images are transferred to advanced Mainland hospitals

Teleconferencing

However, what about Protection, authentication, and annotation of the medical information, etc., ?

Channel Noise, and intentional attacks, such as removal/swapping of Patient's ID

Watermarking applications and Conceivable Attacks

- **Different watermarking applications, usually, faces different types of attacks.**
- **E.g., attacks encountered in Print-to-Web technology are usually different than faced in protecting shared medical information.**
- **Similarly, attacks related to Broadcast monitoring may be different than Secure Digital camera based applications.**
- **Even, in most of the real world watermarking applications, we face a sequence of attacks.**
- **This raises the importance of intelligent and adaptive strategies in Watermarking.**

Machine Learning

- **Machine learning** is concerned with the development of techniques that allow computers to “learn”

- Machine Learning based Schemes gain knowledge through their training phase.

- Once, a trained model is achieved, its performance is evaluated on novel samples

- Examples of Machine Learning techniques are Support vector Machines, Artificial Neural Networks, Decision Tress, Evolutionary Algorithms, etc.

Introduction

- Digital Watermarking

    Watermarking is regarded as the practice of Imperceptibly altering data to embed information about the same data.

Digital Content: Watermarking could be performed on 3D Shapes, printed documents, text, audio, image, video, etc.

Domains: Watermarking could be performed in Spatial, DCT, FFT, Wavelet, etc domains

- **Applications of watermarking:**
    - Ownership assertion
    - Data Authentication
    - Finger Printing
    - Broadcast Monitoring, etc.

Introduction contd..

Main Categorization :

- Robust Watermarking:
  - Watermarks adhere to the image even after it has been attacked
  - Integrity of the watermark itself has to be withheld
- Fragile Watermarking:
  - Watermarks are designed to be destroyed with the slightest modification in the cover work
  - Integrity of the work has to be withheld

Main Characteristics of Watermarking:

- Imperceptibility, Robustness, Capacity, and Security.

Attacks on a watermarked image

- A watermark could be destroyed, removed or stopped from its intended purpose by an attack, which might be intentional or unintentional.
- **Attack Categorization:**
  - No Standard Watermark Attack categorization:
  - Recently, robustness and security based attacks are dealt with separately.
  - For example, robustness based attacks could be:
    - Compression
    - Geometric transformations (horizontal/vertical flipping, rotation, cropping, and scaling)
    - Enhancement techniques (sharpening, low pass filtering, gamma correction, histogram modification)
    - Noise addition

    Security based attacks refer to gaining knowledge about the secrets of the watermarking systems, e.g. Key.

Relevant Research

- Machine Learning (ML) based Watermarking Schemes.
- Fu et al. [1] utilize SVM for optimal detection of a watermark.
- Bounkong et al [2] have proposed independent component analysis based watermarking.
- However, these approaches do not consider the presence of attacks during the training phase and thus are not adaptive.
- In addition, watermarking approaches that do not exploit ML techniques, generally, use simple Threshold Decoding (TD)
- And thus are also not adaptive towards the attack on the watermark [3-4].

Relevant Research contd.

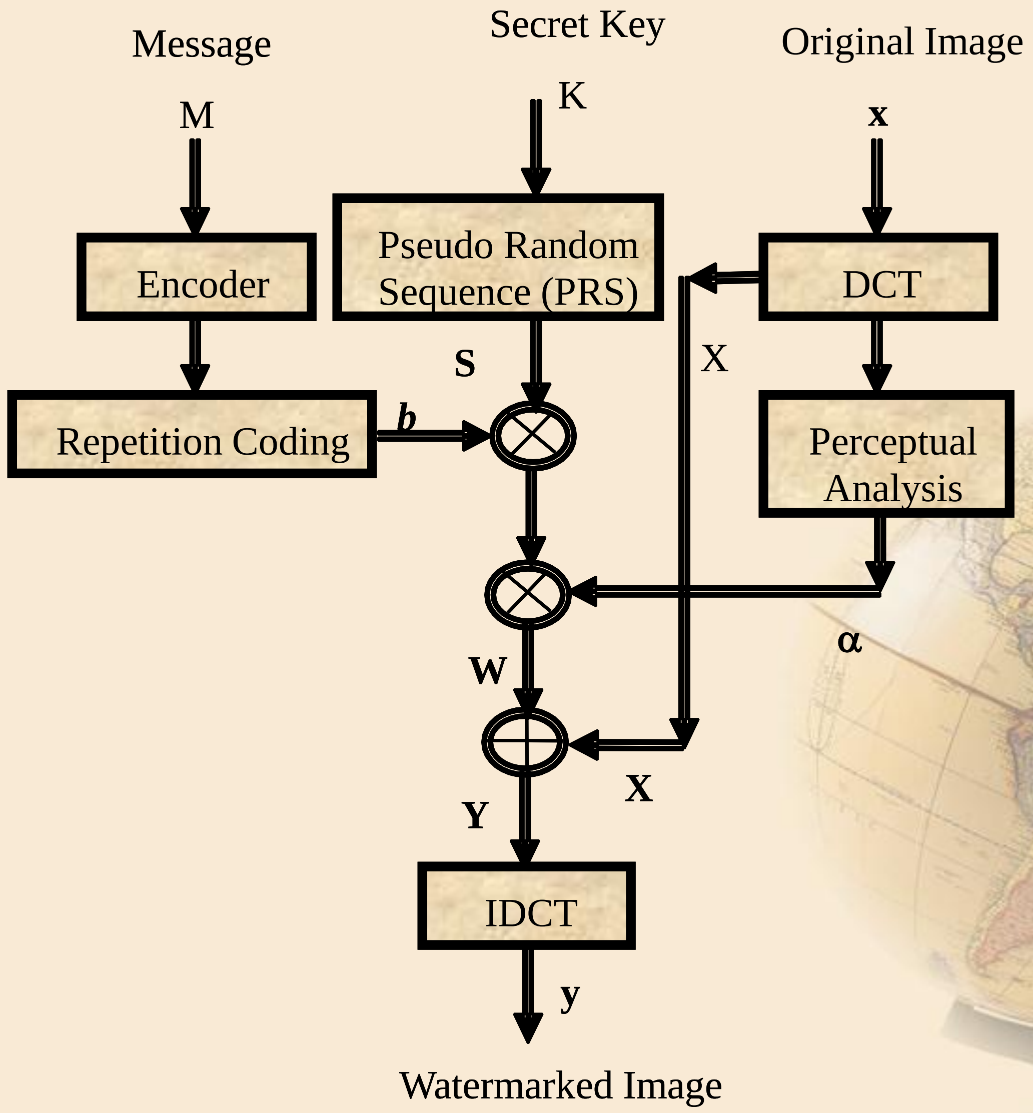
- These approaches neither consider the alterations that may incur to the features
- and nor exploit the individual frequency bands.
- We exploit the individual frequency bands by employing ML models.
- In this way, we are able to gain knowledge pertaining to the distortion
- that might have incurred varyingly on the different frequency bands due to the attack.
- Therefore, our main emphasis is on gaining and exploiting knowledge about distortion.

Introducing a DCT based watermarking Scheme

- We first briefly describe a WM scheme proposed by Hernandez et al.
- This WM approach is used as a base in our proposed scheme, and is extended by using ML techniques.
- Hernandez's WM scheme models the distribution of DCT coefficients in each frequency band as Generalized Gaussian.
- Thereafter, they employ maximum likelihood based estimation to extract the watermark.
- Once the sufficient statistics of the estimation process are computed, a simple threshold is used to decide about the class of bit; $\boldsymbol{b} \in [-1, 1]$

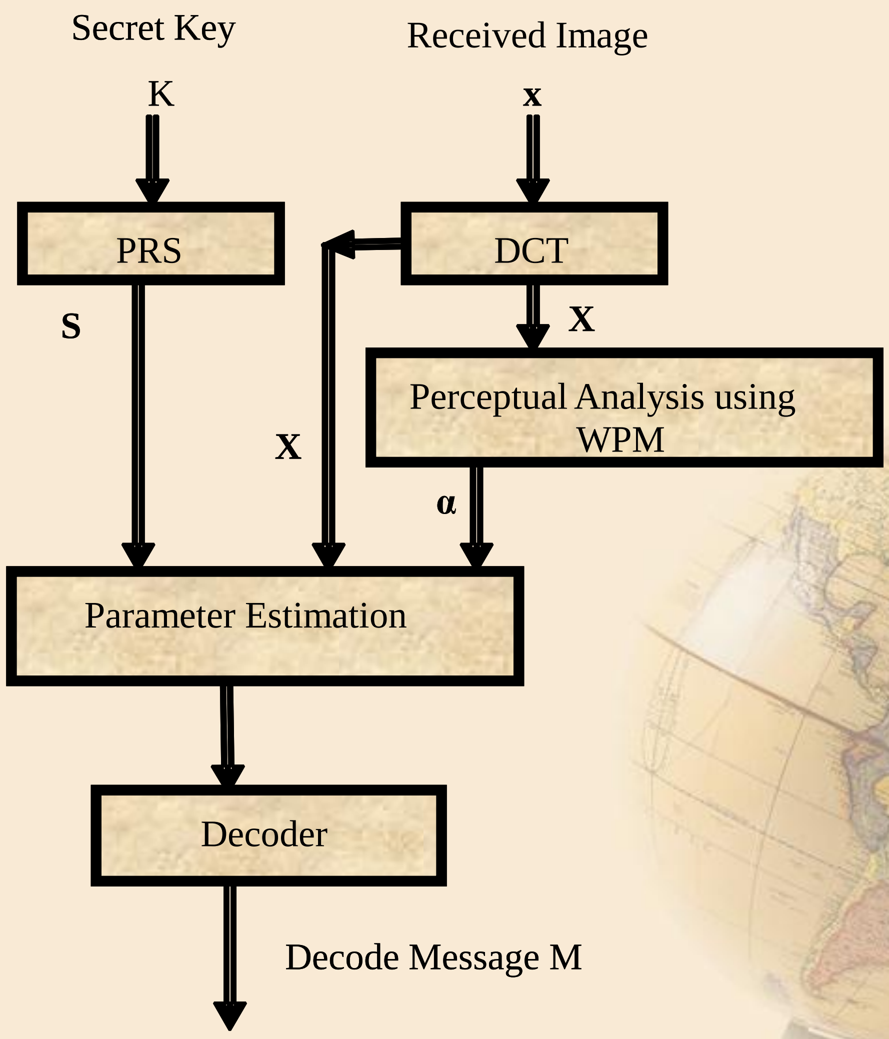
$$\hat{b}_i = \operatorname{sgn}(r_i) \qquad \forall \;\; i \in \{1, 2, \cdots, N\}$$

DCT based Watermarking Scheme



Watermark Embedding Process

DCT based Watermarking Scheme contd.



Watermark Extraction Process

Indices of DCT coefficients in zigzag order of an 8x8 block

0	1	5	6	14	15	27	28
2	4	7	13	16	26	29	42
3	8	12	17	25	30	41	43
9	11	18	24	31	40	44	53
10	19	23	32	39	45	52	54
20	22	33	38	46	51	55	60
21	34	37	47	50	56	59	61
35	36	48	49	57	58	62	63

64 Frequency bands:
Only 22 (7-28) are selected for watermark embedding

Modelling of selected DCT coefficients in zigzag order

256x256 image contains 1024 8x8 blocks

1024 blocks

$$\begin{pmatrix} 7, 8, 9, \ldots\ldots 28 \\ 7, 8, 9, \ldots\ldots 28 \\ 7, 8, 9, \ldots\ldots 28 \\ \vdots \\ 7, 8, 9, \ldots\ldots 28 \end{pmatrix}$$

16 bits: each bit should be repetitively stored in 1024/16= 64 blocks.
But, In each block, 22 frequency bands are selected for embedding, therefore, G_i=64x22

Watermark Embedding and Decoding contd.

The set of coefficients which are sufficient statistics for the ML hidden information decoding process

$$r_i \triangleq \sum_{\boldsymbol{k} \in G_i} \frac{\left|Y[\boldsymbol{k}] + \alpha[\boldsymbol{k}]S[\boldsymbol{k}]\right|^{c[\boldsymbol{k}]} - \left|Y[\boldsymbol{k}] - \alpha[\boldsymbol{k}]S[\boldsymbol{k}]\right|^{c[\boldsymbol{k}]}}{\sigma[\boldsymbol{k}]^{c[\boldsymbol{k}]}}$$

- Where G_i denotes the sample vector of all DCT coefficients in different 8×8 blocks that correspond to a single bit *i*
- For binary antipodal signal, the bits are estimated as:

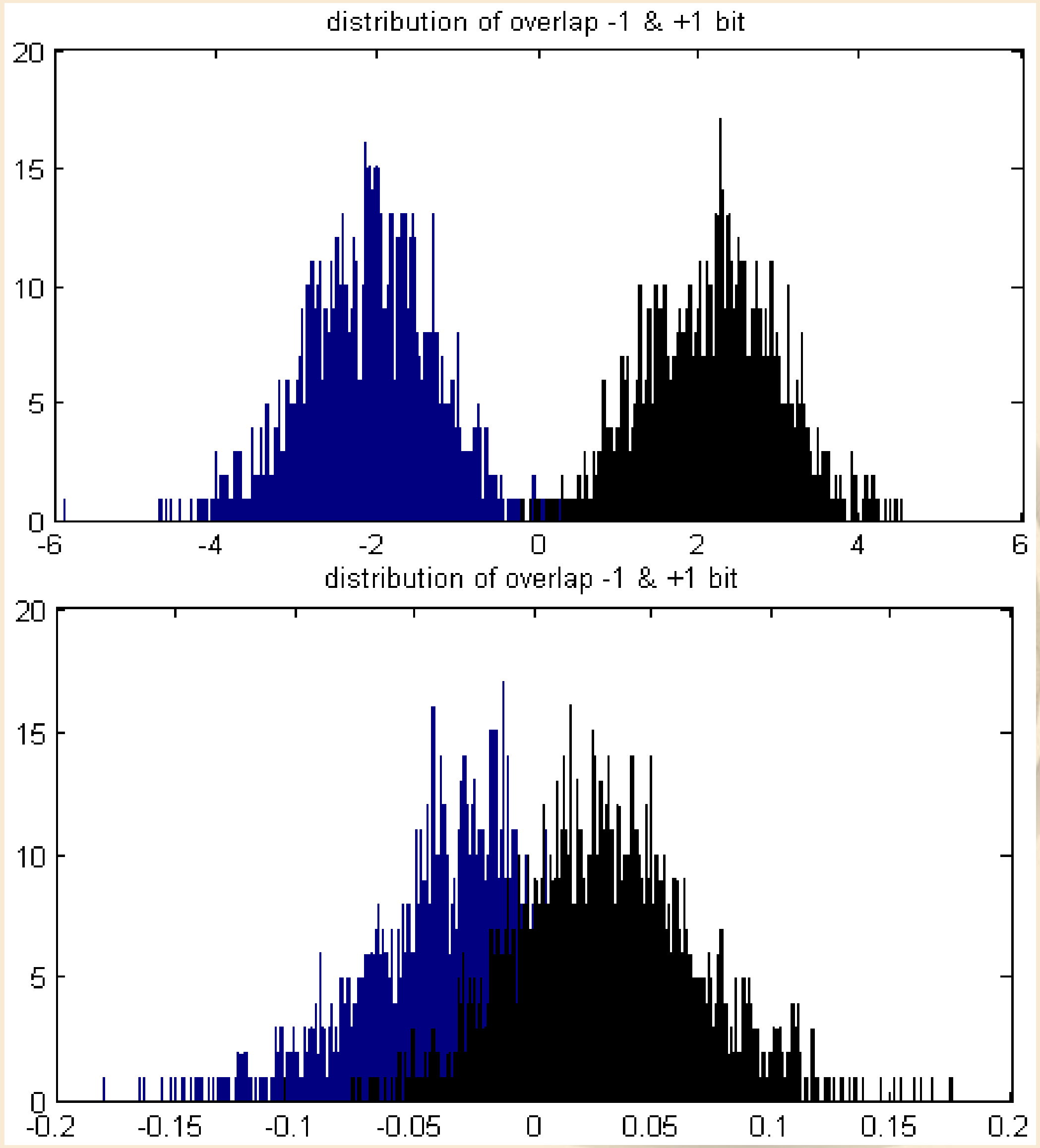
$$\hat{b}_i = \operatorname{sgn}(r_i) \qquad \forall \ i \in \{1, 2, \cdots, N\}$$

Problem Identification

Distribution of sufficient statistics of the maximum likelihood based decoding process

$$\hat{b}_i = \operatorname{sgn}(r_i)$$

No attack



- ✓ **Attack: Gaussian Noise of σ =10**
- ✓ **Simple threshold fails to decode**
- ✓ **ML based decoding is used to exploit its learning capabilities**

Problem Identification and Remedy

- So, firstly, we expected that Machine learning approach, such as, SVM would be better to classify such Data.
- This was expected due to the ability of SVM and ANN to transform a nonlinearly-separable problem into a linearly-separable one
- by transforming the input space into a high dimensional space.
- Secondly, we wanted to analyze the distortion incurred to each frequency band separately.
- Therefore, the ML systems were being fed with 22 dimensional input space.
- This was expected to be more promising than the situation, where all the frequency bands are dealt with collectively.
- Thus providing 22 features corresponding to a single embedded bit.

Assuming independent, but not identically distributed channels

256x256 image contains 1024 8x8 blocks

1024 blocks

7, 8, 9,……………………..............28
7, 8, 9,……………………..............28
7, 8, 9,……………………..............28

.
.
.
.

7, 8, 9,……………………..............28

16 bits: each bit should be repetitively stored in 1024/16= 64 blocks.
In each block, 22 frequency bands are selected for embedding

16 bits: each bit should be repetitively stored in 1024/16= 64 blocks.
But, each frequency band is modeled separately, therefore, G_i^j =64x1

Proposed watermark extraction

In our proposed scheme, in view of the attack,each frequency band is modeled separately

$$r_i = \sum_j r_i^{\,j} \qquad j = 1, 2, \ldots J_{\max}$$

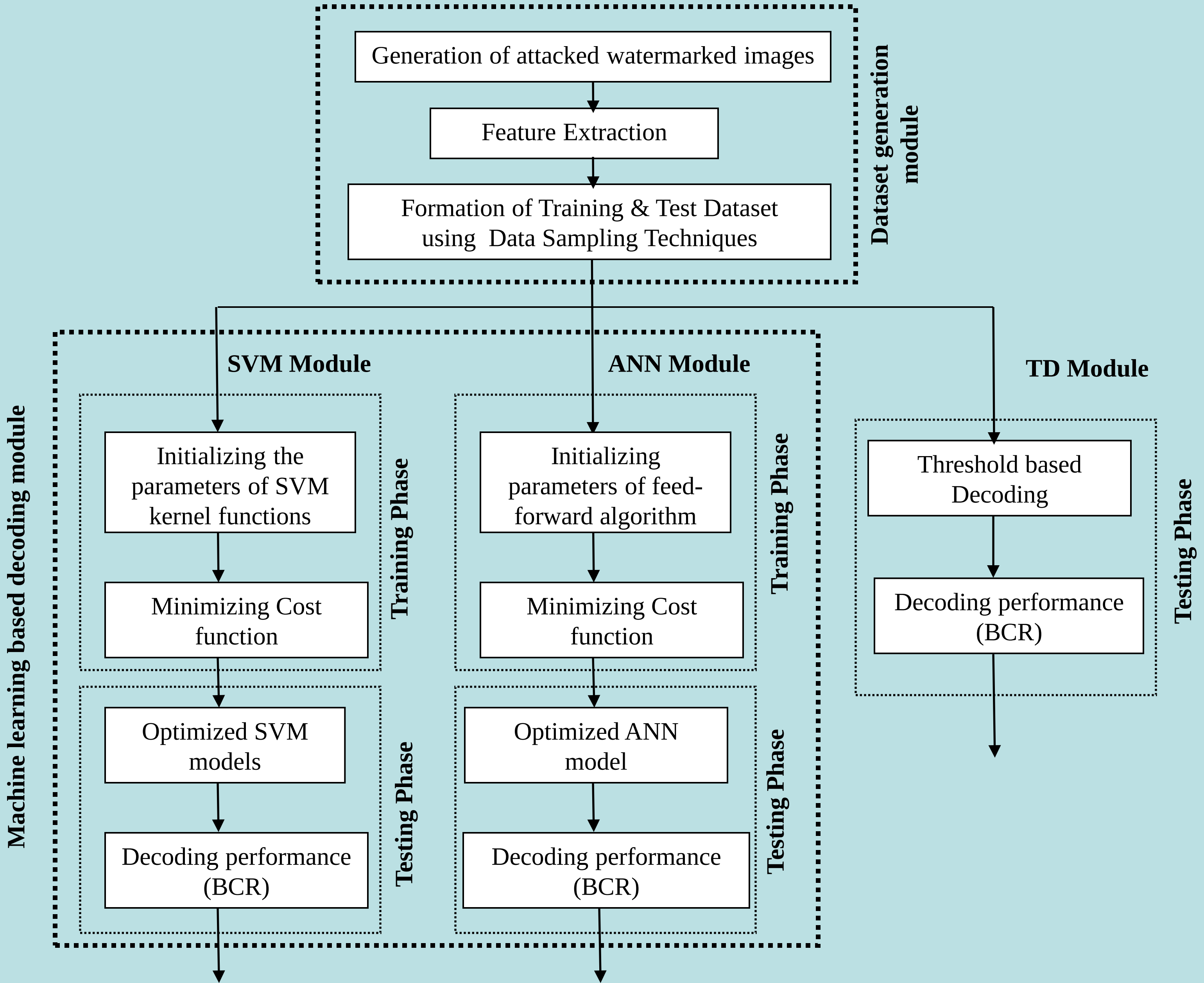
where J_{max} is the maximum number of selected frequency bands, and $r^j{}_i$ is defined as given

$$r_i^{\,j} \triangleq \sum_{\mathbf{k} \in Q_i^j} \frac{\left|Y[\mathbf{k}] + \alpha[\mathbf{k}]s[\mathbf{k}]\right|^{c[\mathbf{k}]} - \left|Y[\mathbf{k}] - \alpha[\mathbf{k}]s[\mathbf{k}]\right|^{c[\mathbf{k}]}}{\sigma[\mathbf{k}]^{c[\mathbf{k}]}}$$

where $Q^j{}_i$, is defined as the sample vector of all DCT coefficients in different 8×8 blocks that correspond to a single bit *i* and the *jth* frequency band.

The values of *c* and σ are estimated from the received watermarked image at the decoding stage.

Basic Block Diagram of our Proposed Scheme


Generation of attacked watermarked images
Feature Extraction
Formation of Training & Test Dataset using Data Sampling Techniques
Dataset generation module
Machine learning based decoding module
SVM Module
ANN Module
TD Module
Initializing the parameters of SVM kernel functions
Minimizing Cost function
Training Phase
Optimized SVM models
Decoding performance (BCR)
Testing Phase
Initializing parameters of feed-forward algorithm
Minimizing Cost function
Training Phase
Optimized ANN model
Decoding performance (BCR)
Testing Phase
Threshold based Decoding
Decoding performance (BCR)
Testing Phase

1st Step: Dataset Generation

- Dataset of 16000 bits
- 5 different images
- Embed message in each image using 25 different keys
- Gaussian noise of σ =10

Type of Images	Gray Scale
Number of images	5
Name of Images	Baboon, Lena, Trees, Boat & couple
Size of images	256 *256
Size of Message	128 bits
Number of keys	25
Type of Attack	Gaussian Attack
Severity of attack	σ =10

1st Step: Dataset Generation (cont…)

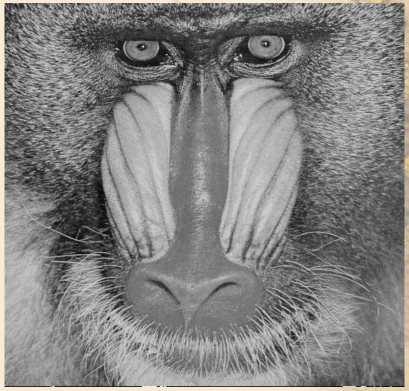
Training Images Set

Lena

Couple

Boat

Trees


Baboon

2^{nd} Step: Feature Selection

- When Watermarked image is attacked
- Message within the image is also corrupted
- Feature Extraction
  - First Method
    - Combine all the statistical coefficients r_i of each bit in message and then sum the number of times that bit is repeated in image.
    - a numerical value corresponding to each bit.
  - Second Method
    - Keep all 22 r_i coefficients as features of the bit
    - Add corresponding r_i of the same channel for the number of times each bit is embedded.
    - 22 features corresponding to each bit

3rd Step: Data Sampling Techniques

- Self Consistency
  - Training and Test data is same
  - In training phase, the class of watermark bit is known.

- Cross Validation
  - Training and Test data is different
  - 4-fold Jackknife Technique
  - Training to test ratio is (3:1)
  - Repeat the process 4 times

4th Step: Performance Measure (BCR)

- Performance of Classification Models is evaluated in terms of Bit Correct Ratio (BCR).
- Ratio between number of Bits correctly predicted and that of total number of Bits.

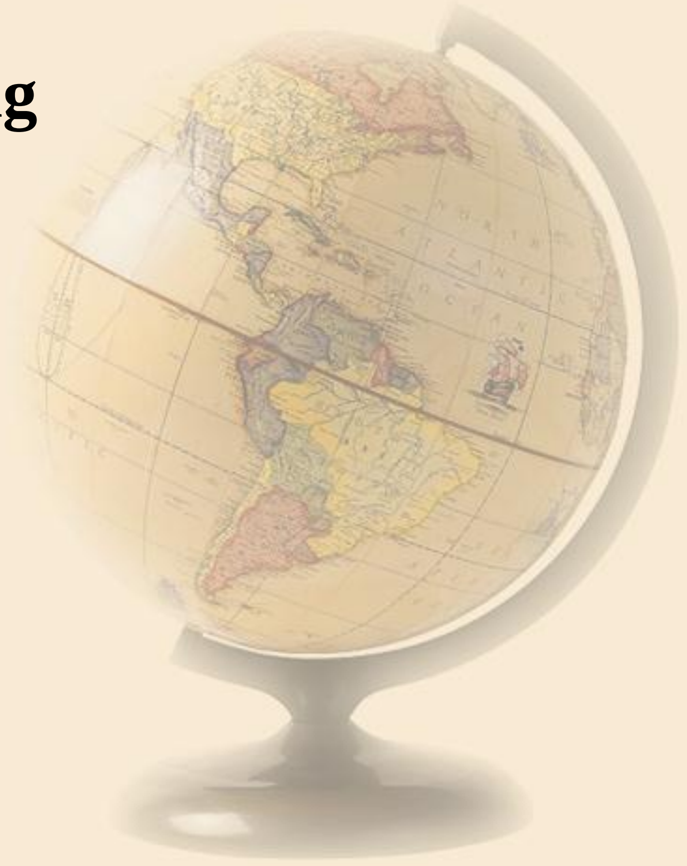
$$BCR(\mathbf{M},\mathbf{M}') = \frac{\sum_{i=1}^{L_m} \overline{(M_i \oplus M_i')}}{L_m}$$

where **M** represents the original, while M' represents the decoded message, L_m is the length of the message and $\oplus$ represents exclusive-OR operation.

Intelligent Decoding Schemes

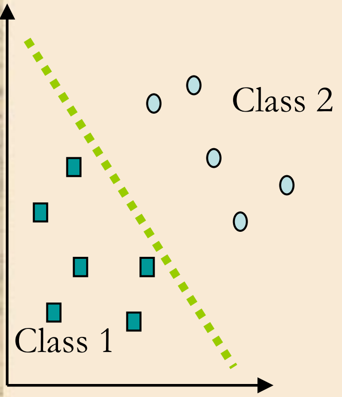
1. **SVM based Decoding**

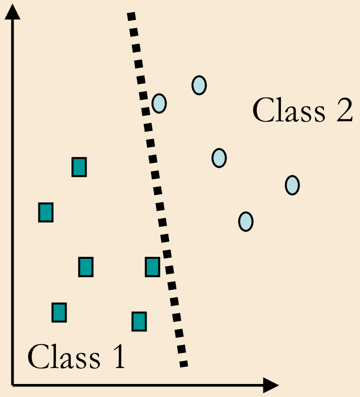
2. **ANN based Decoding**

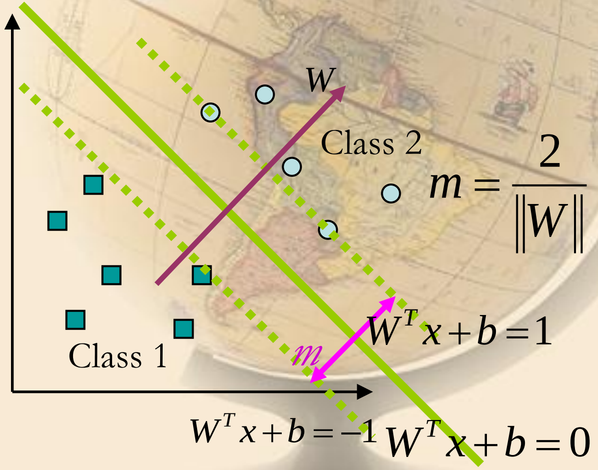


Basics of Support Vector Machine

- Input data mapped into a higher dimension by using dot product of kernel functions.
- Decision boundary should be far away from the data of both classes.







SVM: An Optimization Problem

- For training pairs examples

$$(x_i, c_i),\ x_i \in R^n, c_i \in \{1, -1\},$$

- Decision surface for a linear separable data is :

$$f(x) = \sum_{i=1}^{N} \alpha_i c_i x_i^T . x + b, \alpha_i > 0,$$

- A vector x_i having non zero α_i is called a support vector (SV).
- Decision boundary is determined only by SVs.

- Nonlinear surface:

$$f(x) = \sum_{i=1}^{N_S} \alpha_i c_i K(x_i, x) + b = \sum_{i=1}^{N_S} \alpha_i c_i \Phi(x_i) \cdot \Phi(x) + b$$

SVM Kernel Functions

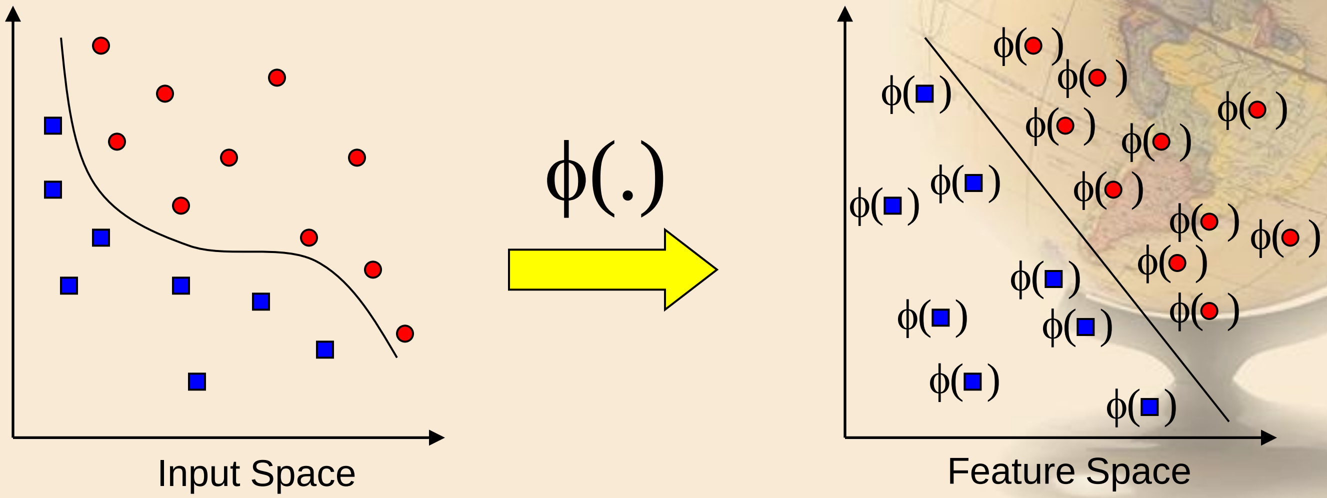
- Kernel function and mapping into higher dimensional space

$K(x_i, x_j) = x_i^T . x_j$, Linear kernel

$K(x_i, x_j) = [\gamma < x_i, x_j > + r\ ]^d$, Polynomials kernel

$K(x_i, x_j) = \exp(-\gamma \| \ x_i - x_j \|^2)$, RBF kernel

- Need of Mapping



1. Details of SVM based Decoding

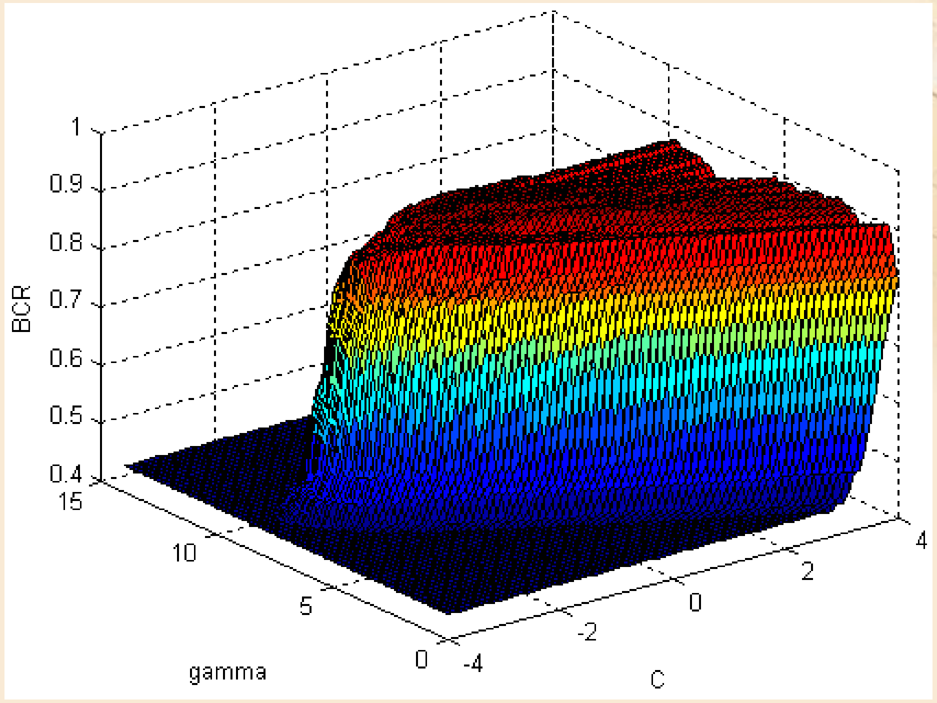
- **Training**
  - SVM classification models are trained for both single as well as 22 features.
  - Two data sampling techniques: self-consistency, cross-validation are used.
  - We used Different SVM kernel functions Linear, Polynomial and RBF.

- **Testing**
  - Trained models are used to test the performance on same or entirely different data.
  - Results from SVM models are used to estimate the decoding performance in terms of BCR.
  - To minimize the problem of over-fitting in the training of SVM classification models, appropriate size of training and testing data is used .

- **Grid Search**
  - The decoding performance of these models is optimized using grid search. Suitable grid range and step size is estimated for SVM kernels.
  - For Poly-SVM, a grid range of C = [2^{-2} to 2^{2}] ,γ = [2^{-2} to 2^{8}] and step size = 0.4
  - For RBF-SVM, C = [2^{-2} to 2^{2}], ΔC =0.4, γ = [2^{-2} to 2^{8}], $\Delta\gamma$ = 0.4.
  - For linear-SVM, C = [2^{-1} to 2^{5}], with ΔC =0.4.

Grid Search for SVM Optimization

- Optimizing different SVM parameters.
- Keep 1st parameter constant for entire range of the 2nd .
- Process is repeated for new values of the 1st parameter.
- In this way, optimal values of both parameters are obtained.



2. Details of ANN Based Decoding

- **ANN models are trained for both single as well as 22 features.**
- **Two data sampling techniques: self-consistency, cross-validation are used.**
- **Levenberg-Marquardt Algorithm is used for training**
- **Important parameters : Number of hidden and output layer units, activation functions and training algorithm.**

ANN		
Features	1	22
Data Size	16000	16000
Epochs	35	25
Hidden layers	3 [8,4,2]	2 [22,11]
Activation function of Hidden Layer	‘tansig’	‘tansig’
Activation function of Output Layer	‘pure linear’	‘pure linear’
Training Algo	Levenberg-Marquardt	Levenberg-Marquardt

Parameters for ANN Based decoding Method

Results and Discussion

1) Implementation Details
2) General Behavior of SVM during Training
3) Self-consistency Performance in terms of BCR
4) Cross-validation Performance in terms of BCR

1). Implementation Details

- Implementation is carried out in MATLAB

- To employ SVM models, MATLAB-based SVM-OSU toolbox is used
- Some of the parameters are optimized using grid search

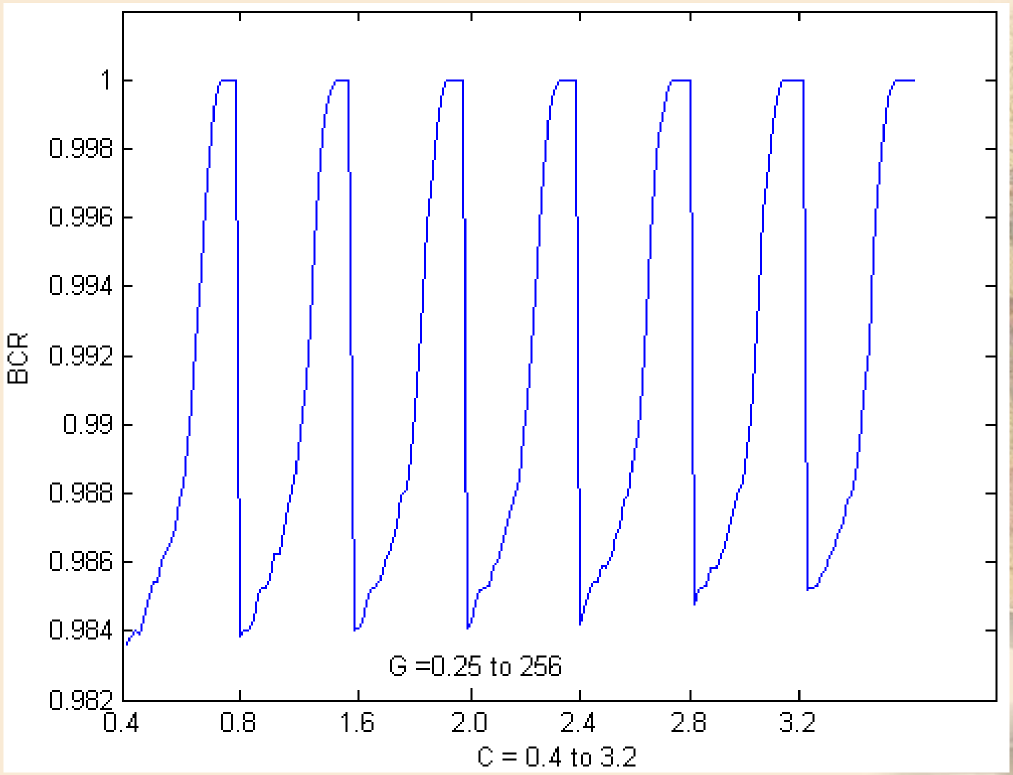
- To develop ANN classification model, MATLAB built-in ANN toolbox is used.

2). General Behavior of SVM Parameter Optimization During Training

- Cyclic Dependency of SVM performance on parameter C
- Accuracy does not increase after achieving

a certain level, whatever is the range

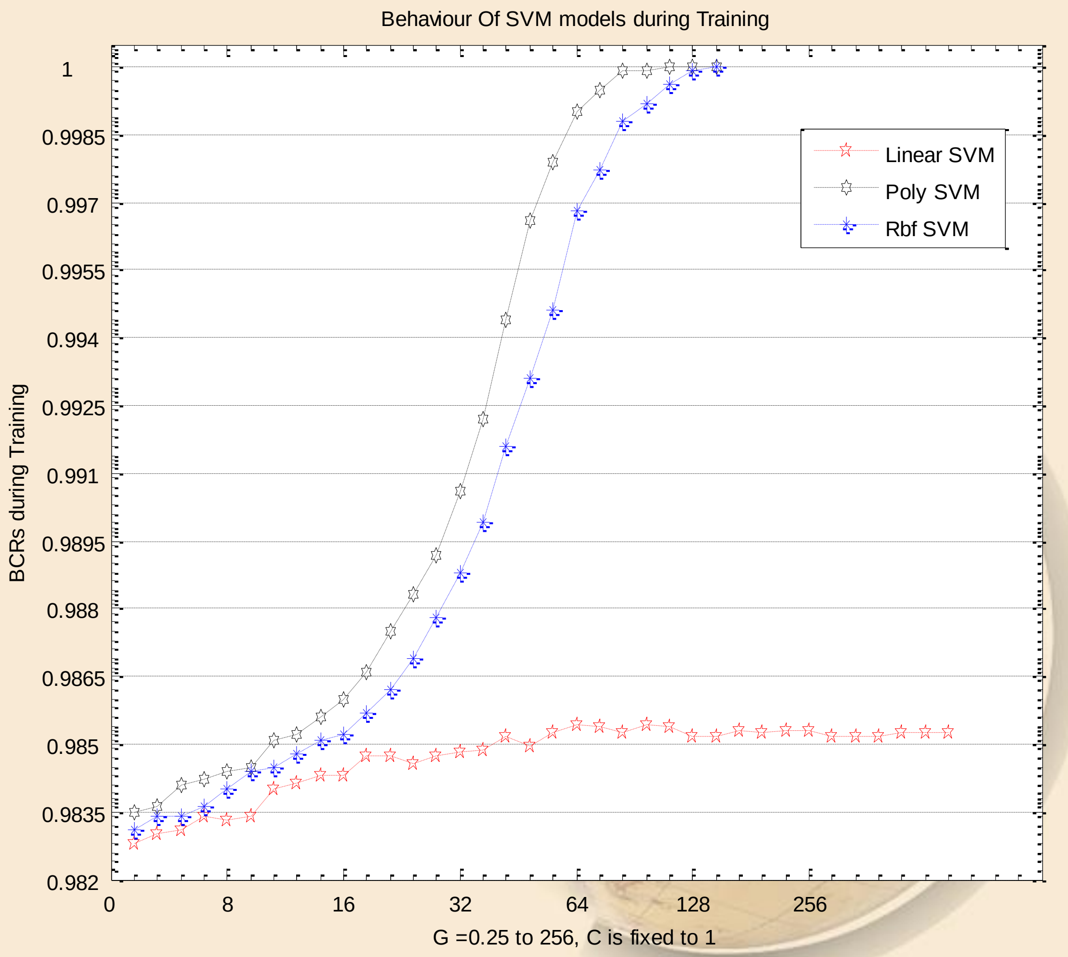
- This helps us in focusing on a short range of C, e.g. 0.4 to 0.8



SVM model Behavior during Grid Search for 22 features

2). General Behavior of SVM during Training (contd…)

- Gamma dependency when C is fixed
- Poly & RBF SVMs forming non linear hyper plane shows improved results
- Poly-SVM optimizes earlier than RBF-SVM

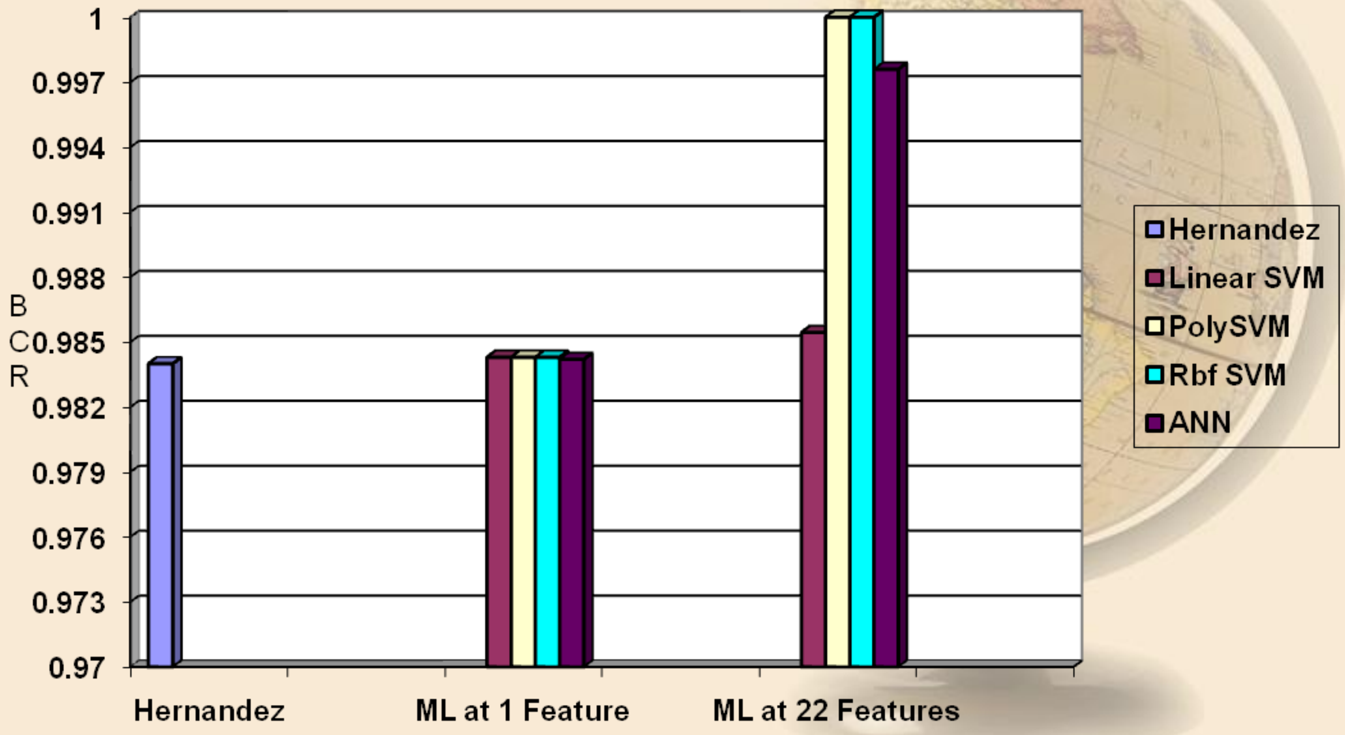


SVM models being trained on 22 features for Self-Consistency

3). Self-Consistency Performance (BCR)

Data Size (bits)	Hernandez Scheme	Proposed SVM based Scheme						ANN	
		Linear		Poly		RBF			
		Number of Features		Number of Features		Number of Features		Number of Features	
		1	**22**	**1**	**22**	**1**	**22**	**1**	**22**
		C=1	C=48	γ=1	γ =1	γ =1	γ =256	Epochs=25	Epochs=25
16000	**0.9840**	**0.9843**	**0.98544**	**0.9843**	**1**	**0.9843**	**1**	**0.9842**	**0.9976**

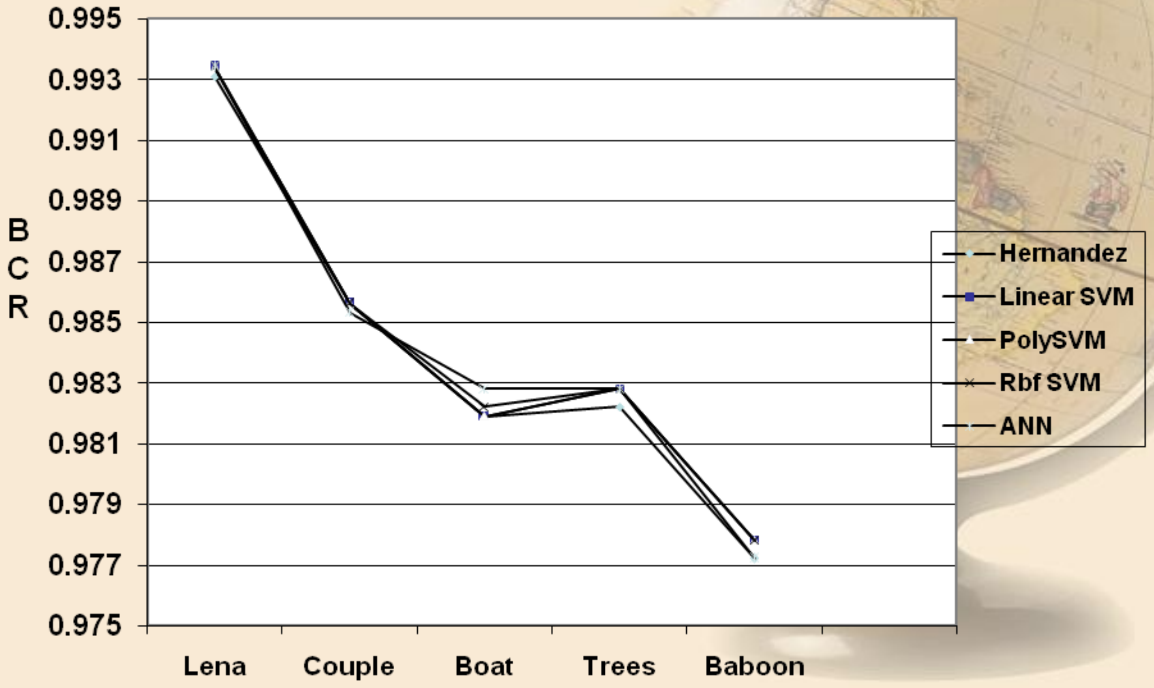
Linear models classify linearly, and therefore, can not classify properly in a high dimensional feature space



3). Self-Consistency Performance using single feature (on different images)

Image Type 25 copies each	Data Size (bits) 128 x 25	Hernandez Scheme	Proposed Scheme			ANN
			Linear $C = 2^{5.6}$	Poly $\gamma = 2^4$	RBF $\gamma = 1$	
Lena	3200	0.9931	0.9934	0.9934	0.9934	0.9934
Boat	3200	0.9819	0.9819	0.9819	0.9819	0.9822
Couple	3200	0.9856	0.9856	0.9856	0.9856	0.9853
Trees	3200	0.9822	0.9828	0.9828	0.9828	0.9828
Baboon	3200	0.9772	0.9778	0.9778	0.9778	0.9772

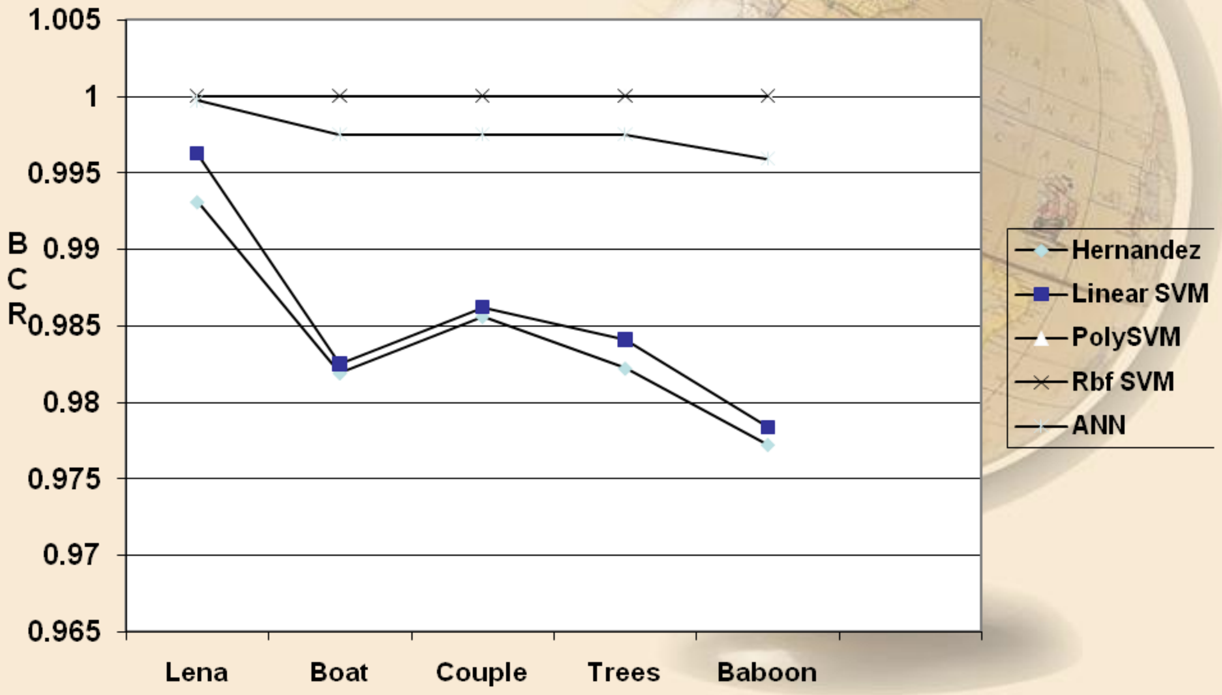
Gaussian noise attack distorts the modeling of DCT coefficients severely in textured image as compared to relatively smooth images



3). Self-Consistency Performance using 22 features (on different images)

Image Type 25 copies each	Data Size (bits) 128 x25	Hernandez Scheme	Proposed Scheme SVM Models			ANN
			Linear C = $2^{5.6}$	Poly $\gamma=2^7$	RBF $\gamma=2^8$	
Lena	3200	0.9931	0.9962	1	1	0.9997
Boat	3200	0.9819	0.9825	1	1	0.9975
Couple	3200	0.9856	0.9862	1	1	0.9975
Trees	3200	0.9822	0.9841	1	1	0.9975
Baboon	3200	0.9772	0.9784	1	1	0.9959

Nonlinear models classify nonlinearly, and therefore, can classify properly in a high dimensional feature space



4). Cross-Validation results: (single feature on train/test data)

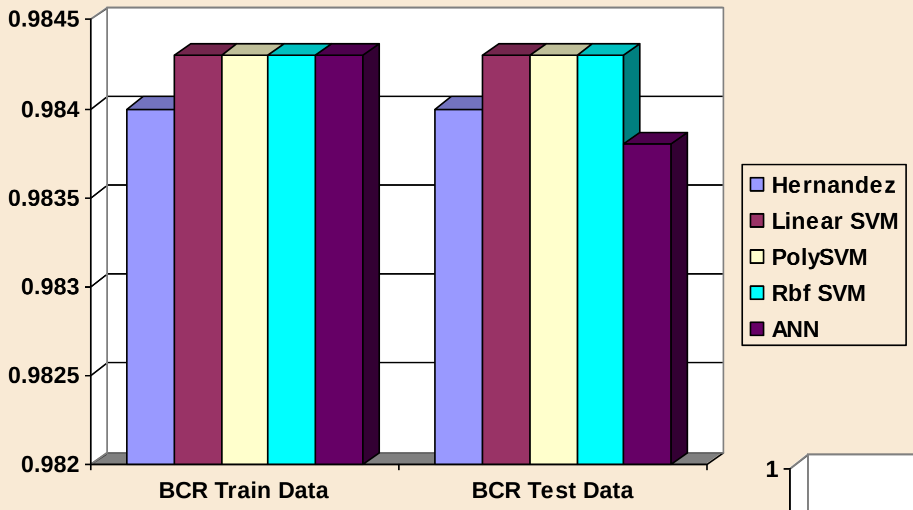
Type of SVM	C	Gamma γ	Training Data (bits)	BCR	Avg. BCR	Test Data (bits)	BCR	Average BCR
Linear	0.5 to 1024	-	4000	0.9832	0.9843	12000	0.9847	0.9843
	0.5 to 1024	-	4000	0.9812		12000	0.9853	
	0.5 to 1024	-	4000	0.9878		12000	0.9832	
	0.5 to 1024	-	4000	0.9850		12000	0.9841	
Poly	0.76 to 1.7	1 to 16	4000	0.9832	0.9843	12000	0.98467	0.9843
	0.76 to 1.7	1 to 16	4000	0.9812		12000	0.98533	
	0.76 to 1.7	1 to 16	4000	0.9878		12000	0.98317	
	0.76 to 1.7	1 to 16	4000	0.9850		12000	0.98408	
RBF	1 to 1.74	1.74 to 16	4000	0.9832	0.9843	12000	0.98467	0.9843
	1 to 1.74	1.74 to 16	4000	0.9812		12000	0.98533	
	1 to 1.74	1.74 to 16	4000	0.9878		12000	0.98317	
	1 to 1.74	1.74 to 16	4000	0.9850		12000	0.98408	
ANN	-	-	4000	0.983	0.9843	12000	0.98433	0.9838
	-	-	4000	0.98175		12000	0.984	
	-	-	4000	0.9875		12000	0.983	
	-	-	4000	0.98475		12000	0.98392	

4). Cross-Validation results: 22 feature (train/test data)

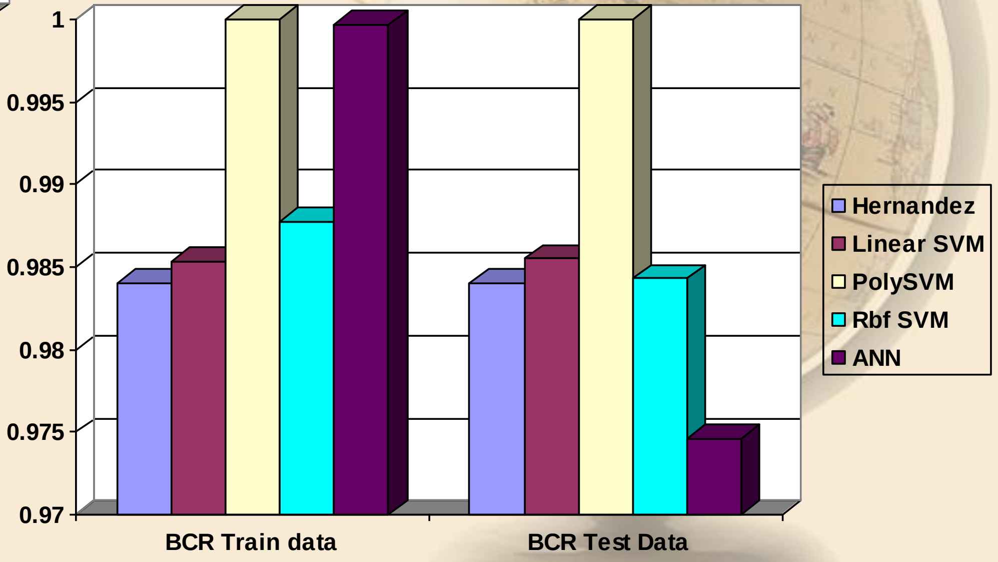
Type of SVM	C	Gamma γ	Training Data (bits)	BCR	Average BCR	Test Data (bits)	BCR	Average BCR
Linear	48.503	-	4000	0.9852	0.9853	12000	0.9855	0.9855
	48.503	-	4000	0.9832		12000	0.98617	
	111.43	-	4000	0.9868		12000	0.9850	
	111.43	-	4000	0.9860		12000	0.98525	
Poly	0.4 to 2	194	4000	1	1	12000	1	1
	0.4 to 2	194	4000	0.9998		12000	1	
	0.4 to 2	194	4000	1		12000	1	
	0.4 to 2	194	4000	1		12000	1	
RBF	0.75786	5.2768	4000	0.9850	0.9877	12000	0.98483	0.9840
	1.3195	6.9644	4000	0.9875		12000	0.98475	
	1	1.7411	4000	0.9868		12000	0.98333	
	2.2974	9.1896	4000	0.9915		12000	0.98325	
ANN	-	-	4000	0.9992	0.9997	12000	0.9762	0.9746
	-	-	4000	0.9998		12000	0.9727	
	-	-	4000	0.9998		12000	0.9768	
	-	-	4000	0.9998		12000	0.9727	
Hernandez	-	-	4000	0.983	0.9840	12000	0.98433	0.9840
	-	-	4000	0.9805		12000	0.98517	
	-	-	4000	0.98775		12000	0.98275	
	-	-	4000	0.98475		12000	0.98375	

4). Cross Validation Performance Comparison (Single & 22 Features)

Cross-validation Performance using single feature



Shows the Generalization of PolySVM



Cross-validation Performance using 22 feature

Conclusion

- We practically demonstrate that the use of ML techniques like SVM attains high performance than traditional decoders in presence of an attack.
- Exploitation of individual frequency bands shows performance improvement
- General order of Performance in terms of BCR is:

  SVM > ANN >Threshold Decoding

  and for different Kernels of SVM:

  PolySVM ≈ RbfSVM > LinearSVM

- When an application of watermarking is changed, and consequently, new attacks are anticipated,
- The re-training of the ML based decoding makes it adaptive by learning the distortion incurred on the features.