# Symbolic Dynamics of Digital Signal Processing Systems 

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## My research interests

## \% Symbolic dynamics

$\alpha_{2}$ Limit cycle, fractal and chaotic behaviors of digital filters with two's complement arithmetic, sigma delta modulators and perceptron training algorithms

* Optimization theory
$\propto_{2}$ Semi-infinite programming, nonconvex optimization and nonsmooth optimization with applications to filter, filter bank, wavelet kernel and pulse designs
* Time frequency analysis
$\alpha_{\infty}$ Nonuniform filter banks, filter banks with block samplers to multimedia and biomedical signal processing
* Control theory
calmpulsive control, optimal control, fuzzy control and chaos control for HIV model and avian influenza model


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## Outline

* Introduction
* Digital filters with two's complement arithmetic
* Sigma delta modulators
* Perceptron training algorithms
* Conclusions
* Q\&A Session


## Introduction

- Definition
aSymbolic dynamics is a kind of system dynamics which involves multi-level signals.
* Motivations
caMany practical signal processing systems, such as digital filters with two's complement arithmetic, sigma delta modulators and perceptron training algorithms, are symbolic dynamical systems. They are found in almost everywhere.


## Introduction

Challenges
œSymbolic dynamical systems could lead to chaotic, fractals and divergent behaviors.
rStability conditions are generally unknown.
@Admissibility conditions are generally unknown.

## Digital filters with two's complement arithmetic

*What are digital filters?
@Digital filters are systems that are characterized in the frequency domain.

$$
H(\omega)=\frac{Y(\omega)}{U(\omega)}
$$

$$
u(k) \longrightarrow \mathrm{h}(\mathrm{k}) \longrightarrow y(k)
$$

$$
U(\omega)=\sum_{\forall k} u(k) e^{-j \omega k} \quad H(\omega)=\sum_{\forall k} h(k) e^{-j \omega k} \quad Y(\omega)=\sum_{\forall k} y(k) e^{-j \omega k}
$$

## Digital filters with two's complement arithmetic Types of digital filters

cosLowpass filters
*Allow a low frequency band of a signal to pass through and attenuate a high frequency band.


## Digital filters with two's complement arithmetic Types of digital filters

$\propto_{3} B a n d p a s s$ filters
*Allow intermediate frequency bands of a signal to pass through and attenuate both low and high frequency bands.
(b)


Frequency $\omega$

## Digital filters with two's complement arithmetic Types of digital filters

caHighpass filters
*Allow a high frequency band of a signal to pass through and attenuate a low frequency band.


## Digital filters with two's complement arithmetic Types of digital filters ๙Band reject filters

\%Allow both low and high frequency bands of a signal to pass through and attenuate intermediate frequency bands.


Frequency $\omega$

## Digital filters with two's

 complement arithmetic Types of digital filterscaNotch filters
*Allow almost all frequency components to pass through but attenuate particular frequencies.


Frequency $\omega$

## Digital filters with two's complement arithmetic Types of digital filters

๙Oscillators
*Allow particular frequency components to pass through and attenuate almost all frequency components.


## Digital filters with two's complement arithmetic Types of digital filters <br> caAllpass filters

 *Allow all frequency components to pass through.(g)


Frequency $\omega$

## Digital filters with two's complement arithmetic

* Hardware schematic



## Digital filters with two's complement arithmetic

* When no input is present, the filter can be described by the following nonlinear state space difference equation:

$$
\begin{aligned}
& \mathbf{x}(k+1) \equiv\left[\begin{array}{l}
x_{1}(k+1) \\
x_{2}(k+1)
\end{array}\right]=\mathrm{F}(\mathbf{x}(k)) \\
& =\left(\left[\begin{array}{c}
x_{2}(k) \\
f\left(b \cdot x_{1}(k)+a \cdot x_{2}(k)\right)
\end{array}\right]\right)
\end{aligned}
$$

Direct form

# Digital filters with two's complement arithmetic 

where $f(\bullet)$ is the nonlinear function associated with the two's complement arithmetic


Overflow
No overflow
Overflow

# Digital filters with two's 

 complement arithmetic$\mathbf{x}(k+1)=\mathbf{A} \cdot\left[\begin{array}{l}x_{1}(k) \\ x_{2}(k)\end{array}\right]+\left[\begin{array}{l}0 \\ 2\end{array}\right] \cdot s(k)$
where $\mathbf{A}=\left[\begin{array}{ll}0 & 1 \\ b & a\end{array}\right]$

$$
\begin{aligned}
& {\left[\begin{array}{l}
x_{1}(k) \\
x_{2}(k)
\end{array}\right] \in I^{2} \equiv\left\{\left(x_{1}, x_{2}\right):-1 \leq x_{1}<1,-1 \leq x_{2}<1\right\}} \\
& s(k) \in\{-m, \cdots,-1,0,1, \cdots, m\}
\end{aligned}
$$

and $m$ is the minimum integer satisfying

$$
-2 \cdot m-1 \leq b \cdot x_{1}+a \cdot x_{2} \leq 2 \cdot m+1
$$

## Digital filters with two's

 complement arithmetic $s(k)$ is called symbolic sequences.$$
\begin{aligned}
& s(k)=1 \Rightarrow-3 \leq b \cdot x_{1}(k)+a \cdot x_{2}(k)<-1 \\
& s(k)=0 \Rightarrow-1 \leq b \cdot x_{1}(k)+a \cdot x_{2}(k)<1 \\
& s(k)=-1 \Rightarrow 1 \leq b \cdot x_{1}(k)+a \cdot x_{2}(k)<3
\end{aligned}
$$

# Digital filters with two's complement arithmetic 

For example: $\mathbf{x}(0)=\left[\begin{array}{ll}-0.6135 & 0.6135\end{array}\right]^{T}, b=-1$ and $a=0.5$ $b \cdot x_{1}(0)+a \cdot x_{2}(0)=0.9203 \Rightarrow s(0)=0$ $b \cdot x_{1}(1)+a \cdot x_{2}(1)=-0.1534 \Rightarrow s(1)=0$

Two's complement value
$b \cdot x_{1}(14)+a \cdot x_{2}(14)=1.0018 \Rightarrow s(14)=-1$ and $x_{2}(15)=-0.9982$
$b \cdot x_{1}(15)+a \cdot x_{2}(15)=-0.7597 \Rightarrow s(15)=0$
$b \cdot x_{1}(16)+a \cdot x_{2}(16)=0.6184 \Rightarrow s(16)=0$
$b \cdot x_{1}(17)+a \cdot x_{2}(17)=1.0689 \Rightarrow s(17)=-1$ and $x_{2}(18)=-0.9311$
$b \cdot x_{1}(18)+a \cdot x_{2}(18)=-1.0839 \Rightarrow s(18)=1$ and $x_{2}(19)=0.9161$
$s=\left(\begin{array}{llllllllll}0 & 0 & \cdots & 0 & -1 & 0 & 0 & -1 & 1 & \cdots\end{array}\right)$

## Digital filters with two's complement arithmetic

*Stability analysis of the corresponding linear system œEEigenvalues of $\mathbf{A}$

$$
\lambda=\frac{a \pm \sqrt{a^{2}+4 \cdot b}}{2}
$$

## Digital filters with two's complement arithmetic



# Digital filters with two's complement arithmetic 

$\cos _{5} \mathbf{R}_{5}$ :Magnitudes of both eigenvalues $<1$.
$\Rightarrow$ The corresponding linear system is stable.
$\infty \mathbf{R}_{\mathbf{1}}$ and $\mathbf{R}_{\mathbf{3}}$ : Either one of the magnitudes of the eigenvalues < 1 .
$\Rightarrow$ The corresponding linear system is unstable.
$\infty_{3} \mathbf{R}_{\mathbf{2}}$ and $\mathbf{R}_{\mathbf{4}}$ :Magnitudes of both eigenvalues are greater than 1.
$\Rightarrow$ The corresponding linear system is unstable.

## Digital filters with two's complement arithmetic

* Effects of different initial conditions when the eigenvalues of system matrix are on the unit circle caType I trajectory
:There is a single rotated and translated ellipse in the phase portrait.

$$
a=0.5, b=-1, x(0)=\left[\begin{array}{c}
0.612 \\
-0.612
\end{array}\right]
$$

## Digital filters with two's complement arithmetic



## Digital filters with two's complement arithmetic

caType II trajectory
*There are some rotated and translated ellipses in the phase portrait.

$$
a=0.5, b=-1, x(0)=\left[\begin{array}{c}
0.616 \\
-0.616
\end{array}\right]
$$

## Digital filters with two's complement arithmetic



This corresponds to the limit cycle behavior.

## Digital filters with two's complement arithmetic

casType III trajectory
*There is a fractal pattern on the phase portrait.

$$
a=0.5, b=-1, x(0)=\left[\begin{array}{c}
0.6135 \\
-0.6135
\end{array}\right]
$$

## Digital filters with two's complement arithmetic


$\mathrm{c}_{3}$ Conclusion: Very sensitive to initial conditions

## Digital filters with two's complement arithmetic

* Step response of second order digital filters with two's complement arithmetic
$\infty_{3}$ The system can be represented as:
$\mathbf{x}(k+1)=\left(\left[\begin{array}{c}x_{2}(k) \\ f\left(b \cdot x_{1}(k)+a \cdot x_{2}(k)+u(k)\right)\end{array}\right]\right)$
$=\mathbf{A} \cdot\left[\begin{array}{l}x_{1}(k) \\ x_{2}(k)\end{array}\right]+\mathbf{B} \cdot u(k)+\left[\begin{array}{l}0 \\ 2\end{array}\right] \cdot s(k)$
where $\mathbf{A}=\left[\begin{array}{ll}0 & 1 \\ b & a\end{array}\right]$ and $\mathbf{B}=\left[\begin{array}{l}0 \\ 1\end{array}\right]$
$\Rightarrow$ DC offset on symbolic sequences.


## Digital filters with two's complement arithmetic

For $a=-1.5, b=-1, c=1, \mathbf{x}(0)=\left[\begin{array}{l}0.3 \\ 0.3\end{array}\right]$


## Digital filters with two's complement arithmetic

For $a=-1.5, b=-1$ and $c=1$


## Digital filters with two's complement arithmetic

For $a=-1.5, b=-1, c=1, \mathbf{x}(0)=\left[\begin{array}{l}-0.7 \\ -0.7\end{array}\right], s=(0,-1,-1,0, \cdots)$


## Digital filters with two's complement arithmetic

For $a=-1.5, b=-1$ and $c=1$


## Digital filters with two's complement arithmetic

For $a=-1.5, b=-1, c=1, \mathbf{x}(0)=\left[\begin{array}{l}-0.99 \\ -0.99\end{array}\right]$


## Digital filters with two's complement arithmetic

For $a=-1.5, b=-1$ and $c=1$


## Digital filters with two's complement arithmetic

* Sinusoidal response of second order digital filters with two's complement arithmetic




## Digital filters with two's complement arithmetic






## Digital filters with two's complement arithmetic

 * Autonomous case when the eigenvalues of A are inside the unit circlePhase portrait with $\mathrm{a}=0.5, \mathrm{~b}=-0.99, \mathrm{x}=[0.6135-0.6135]$


## Digital filters with two's complement arithmetic



## Digital filters with two's complement arithmetic



## Digital filters with two's

 complement arithmetic* Autonomous case for third order digital filters with two's complement arithmetic realized in cascade form
œSystem block diagram:



## Digital filters with two's complement arithmetic



## Digital filters with two's complement arithmetic




## Digital filters with two's

 complement arithmetic* Autonomous case for third-order digital filters with two's complement arithmetic realized in parallel form
œSystem block diagram:



# Digital filters with two's complement arithmetic 



## Digital filters with two's complement arithmetic



## Digital filters with two's complement arithmetic

* Admissibility of second order digital filters with two's complement arithmetic
cadmissible set of periodic symbolic sequences is defined as a set of periodic symbolic sequences such that there exists an initial condition that produces the symbolic sequences.

Set of initial conditions Admissible set of periodic symbolic sequences


## Digital filters with two's complement arithmetic

For example, when $a=0.5, b=-1, c=0$,

| $M$ | Admissible $s$ |
| :---: | :---: |
| 1 | $s=(0, \cdots)$ |
| 2 | $s=(-1,1, \cdots) s=(1,-1, \cdots)$ |
| 3 | $s=(0,0,1, \cdots) s=(0,1,0, \cdots)$ |
|  | $s=(1,0,0, \cdots) s=(-1,0,0, \cdots)$ |
|  | $s=(0,0,-1, \cdots) s=(0,-1,0, \cdots)$ |
| 15 | Not found |

Not admissible $s$
$s=(1, \cdots) s=(-1, \cdots)$
$s=(1,0, \cdots) s=(0,1, \cdots)$
$s=(-1,0, \cdots) s=(0,-1, \cdots)$
$s=(0,1,1, \cdots) s=(0,1,-1, \cdots)$
$s=(0,-1,1, \cdots) s=(0,-1,-1, \cdots)$
$s=(1,0,1, \cdots) \quad s=(1,0,-1, \cdots)$
$s=(1,-1,0, \cdots) s=(1,-1,0, \cdots)$

## Digital filters with two's complement arithmetic

A periodic sequence $s$ with period $M$ is admissible if and only if for $i=0,1, \cdots, M-1$

$$
-1 \leq \frac{\sum_{j=0}^{M-1} s(\bmod (i+j, M)) \cdot \cos \left(\left(\frac{M}{2}-j-1\right) \cdot \theta\right)}{\sin \left(\frac{M \cdot \theta}{2}\right) \cdot \sin \theta}<1
$$

## Sigma delta modulators

*What is sigma delta modulators?
aSigma delta modulators are devices implementing sigma delta modulations and are widely used in analogue-to-digital conversions.
©TThe input signals are first oversampled to obtain the inputs of the sigma delta modulators. The loop filters are to separate the quantization noises and the input signals so that very high signal-to-noise ratios could be achieved at very coarse quantization schemes.

## Sigma delta modulators

*Block diagram


$$
\begin{aligned}
& \frac{S(z)}{U(z)}=\frac{F(z)}{1+F(z)} \\
& \frac{S(z)}{N(z)}=\frac{1}{1+F(z)}
\end{aligned}
$$

## Sigma delta modulators

*Nonlinear state space dynamical model:

$$
\begin{aligned}
& \mathrm{F}(z)=\frac{2 \cos \theta z^{-1}-z^{-2}}{1-2 \cos \theta z^{-1}+z^{-2}} \\
& \Rightarrow y(k)-2 \cos \theta y(k-1)+y(k-2) \\
& =2 \cos \theta(u(k-1)-Q(y(k-1)))-(y(k-2)-Q(y(k-2))) \\
& \Rightarrow y(k)=2 \cos \theta y(k-1)-y(k-2)+ \\
& 2 \cos \theta(u(k-1)-Q(y(k-1)))-(y(k-2)-Q(y(k-2))) \\
& \mathbf{u}(k) \equiv\left[\begin{array}{ll}
u(k-2) & u(k-1)
\end{array}\right]^{T} \\
& \mathbf{x}(k) \equiv\left[\begin{array}{ll}
y(k-2) & y(k-1)
\end{array}\right]^{T} \\
& \mathbf{s}(k) \equiv\left[\begin{array}{ll}
Q(y(k-2)) & Q(y(k-1))
\end{array}\right]^{T}
\end{aligned}
$$

## Sigma delta modulators

$$
\begin{aligned}
\mathbf{A} \equiv & {\left[\begin{array}{cc}
0 & 1 \\
-1 & 2 \cos \theta
\end{array}\right] \quad \mathbf{B} \equiv\left[\begin{array}{cc}
0 & 0 \\
-1 & 2 \cos \theta
\end{array}\right] } \\
& \mathbf{x}(k+1)=\mathbf{A x}(k)+\mathbf{B}(\mathbf{u}(k)-\mathbf{s}(k)) \\
& Q(y) \equiv\left\{\begin{array}{cc}
1 & y \geq 0 \\
-1 & \text { otherwise }
\end{array}\right.
\end{aligned}
$$

*There are only finite numbers of possibilities of $s(k)$. Hence, $s(k)$ can be viewed as symbol and $s(k)$ is called a symbolic sequence.

## Sigma delta modulators

* Second order marginally stable bandpass sigma delta modulators



## Sigma delta modulators



## Sigma delta modulators

* Second order strictly stable bandpass sigma delta modulators



## Sigma delta modulators



## Sigma delta modulators



## Sigma delta modulators

* General second order bandpass sigma delta modulators








## Sigma delta modulators

* Admissibility of periodic sequence

$$
\begin{aligned}
& \zeta \equiv\left[\begin{array}{llc}
s_{1}(0), & s_{2}(0), & \cdots \\
s_{1}(M-1), & s_{2}(M-1)
\end{array}\right]^{T} \\
& \mathbf{D}_{j} \equiv\left[\begin{array}{cc}
d \sin j \theta & c \sin j \theta \\
d \sin (j+1) \theta & c \sin (j+1) \theta
\end{array}\right]
\end{aligned}
$$

$$
\mathbf{D} \equiv\left[\begin{array}{ccccc}
\mathbf{D}_{M-1} & \mathbf{D}_{M-2} & \cdots & \mathbf{D}_{1} & \mathbf{D}_{0} \\
\mathbf{D}_{0} & \mathbf{D}_{M-1} & \ddots & & \mathbf{D}_{1} \\
\vdots & \ddots & \ddots & \ddots & \vdots \\
\vdots & & \ddots & \mathbf{D}_{M-1} & \mathbf{D}_{M-2} \\
\mathbf{D}_{M-2} & \cdots & \cdots & \mathbf{D}_{0} & \mathbf{D}_{M-1}
\end{array}\right]
$$

# Sigma delta modulators <br> $\mathbf{K} \equiv \operatorname{diag}\left(\left(\mathbf{I}-\mathbf{A}^{M}\right)^{-1}, \cdots, \quad\left(\mathbf{I}-\mathbf{A}^{M}\right)^{-1}\right)$ 

$\mathbf{v} \equiv\left[\frac{(d+c) \bar{u}}{\sin \theta} \sum_{j=0}^{M-1} \sin j \theta, \quad \frac{(d+c) \bar{u}}{\sin \theta} \sum_{j=1}^{M} \sin j \theta\right]$
$\boldsymbol{\tau} \equiv\left[\begin{array}{lll}\mathbf{v}, & \cdots, & \mathbf{v}\end{array}\right]^{T}$
$\mathbf{s} \equiv(\mathbf{s}(0), \mathbf{s}(1), \cdots, \mathbf{s}(M-1))$
$\mathfrak{c} \Sigma$ be the admissible set of periodic output sequences with period M
$\Sigma=\{\mathbf{s}: \mathbf{Q}(\mathbf{K}(\mathbf{D} \zeta+\boldsymbol{\tau}))=\zeta\}$

## Perceptron training algorithms

 What is a perceptron training algorithm?*A perceptron is a single neuron that employs a single bit quantization function as its activation

$$
\begin{aligned}
& \text { function. } \\
& x_{1}(k) \xrightarrow{\longrightarrow} w_{1}(k) \\
& x_{d}(k) \longrightarrow \otimes w_{d}(k) \\
& y(k)=Q\left(\mathbf{w}^{T}(k) \mathbf{x}(k)\right)^{w_{0}(k)} \\
& \mathbf{x}(k) \equiv\left[\begin{array}{lll}
1, & x_{1}(k), & \cdots, \\
x_{d}(k)
\end{array}\right]^{T} \\
& \text { where } \mathbf{w}(k) \equiv\left[w_{0}(k), \quad w_{1}(k), \quad \cdots, \quad w_{d}(k)\right]^{T} \\
& Q(z) \equiv\left\{\begin{array}{cc}
1 & z \geq 0 \\
-1 & z<0
\end{array}\right.
\end{aligned}
$$

## Perceptron training algorithms

*What is a perceptron training algorithm?
$*$ The weights of a perceptron is usually found by the perceptron training algorithm.

$$
\mathbf{w}(k+1)=\mathbf{w}(k)+\frac{t(k)-y(k)}{2} \mathbf{x}(k)
$$

where $t(k)$ is the desired output corresponding to $x(k)$.
\& $\mathrm{lf}(\mathrm{k})$ converges, then the steady state value of $w(k)$ could be employed as the weights of the perceptron.

## Perceptron training algorithms

@Example 1

$$
\mathbf{w}(k+1)=\mathbf{w}(k)+\frac{t(k)-y(k)}{2} \mathbf{x}(k)
$$

| Iteration index $k$ | $\mathbf{w}_{\text {old }}(k)$ | $\mathbf{x}(k)$ | $t(k)$ | $y(k)$ | $\mathbf{w}_{\text {new }}(k)$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 0 | $\left[\begin{array}{llll}0 & 0 & 0\end{array}\right]^{\mathrm{T}}$ | [1515 1$]^{\mathrm{T}}$ | -1 | 1 | $[-1-5-1]^{\mathrm{T}}$ |
| 1 | $[-1-5-1]^{\mathrm{T}}$ |  | -1 | -1 | $[-1-5-1]^{\mathrm{T}}$ |
| 2 | $[-1-5-1]^{\mathrm{T}}$ | $\left[\begin{array}{lllll}1 & 1 & 1\end{array}\right]^{\mathrm{T}}$ | 1 | -1 | [0-4 0) ${ }^{\mathrm{T}}$ |
| 3 | [0-4 0) ${ }^{\mathrm{T}}$ | $\left[_{1}^{1} 303\right]^{\text {T }}$ | 1 | -1 | $\left[\begin{array}{lllll}1 & -1 & 3\end{array}\right]^{\mathrm{T}}$ |
| 4 | $\left[\begin{array}{llll}1 & -1\end{array}\right]^{\mathrm{T}}$ | $\left[\begin{array}{llll}1 & 4\end{array}\right]^{\mathrm{T}}$ | -1 | 1 | [0-5 1 $]^{\mathrm{T}}$ |
| 5 | [0-5 1 1 ${ }^{\mathrm{T}}$ | $\left[\begin{array}{llll}1 & 2 & 3\end{array}\right]^{\mathrm{T}}$ | 1 | -1 | [1-3 4] ${ }^{\mathrm{T}}$ |
| $6 \rightarrow N /$ | $\left[\begin{array}{lll}1-3 & 4\end{array}\right]^{\mathrm{T}}$ | [151] ${ }^{\text {T }}$ | -1 | -1 | $\left[\begin{array}{llll}1 & -3\end{array}\right]^{\mathrm{T}}$ |
| $7 \sim$ | $\left[\begin{array}{lll}1 & -3 & 4\end{array}\right]^{\mathrm{T}}$ | $\left[\begin{array}{llll}1 & 2 & 1\end{array}\right]^{\mathrm{T}}$ | -1 | -1 | $[1-34]^{T}$ |
| $85$ | $\left[\begin{array}{llll}1 & -3\end{array}\right]^{\mathrm{T}}$ | $\left[\begin{array}{llll}1 & 1 & 1\end{array}\right]^{\mathrm{T}}$ | 1 | 1 | [1-34] ${ }^{\text {T }}$ |
| $9 \& \text { Converge }$ | $[1-34]^{\mathrm{T}}$ | $\left[\begin{array}{llll}1 & 3 & 3\end{array}\right]^{\mathrm{T}}$ | 1 | 1 | $[1-34]^{\mathrm{T}}$ |
| $10 Z_{2}$ | [1-3 4, ${ }^{\text {T }}$ | $\left[\begin{array}{llll}1 & 4 & 2\end{array}\right]^{\text {T }}$ | -1 | -1 | $\left[\begin{array}{llll}1 & -3\end{array}\right]^{\mathrm{T}}$ |
| 11 UNNN | $[1-34]^{T}$ | $\left[\begin{array}{llll}1 & 2 & 3\end{array}\right]^{\mathrm{T}}$ | 1 | 1 | $[1-34]^{T}$ |

## Perceptron training algorithms

csExample 1


## Perceptron training algorithms

asExample 2

$$
\mathbf{w}(k+1)=\mathbf{w}(k)+\frac{t(k)-y(k)}{2} \mathbf{x}(k)
$$



## Perceptron training algorithms

cexample 2


## Perceptron training algorithms asxample 3





## Perceptron training algorithms

* Example 4
$\propto$ The set of training feature vectors $\infty$ Desirable output $\{1,-1,1,-1\}$
calnitial weight $\mathbf{w}(0)=\left[\begin{array}{ll}-1, & -1, \\ \hline\end{array}\right]^{T}$
$\underset{\sim}{\infty}$ Result: $\mathbf{w}(k)=\left[\begin{array}{lll}0, & 2, & 0\end{array}\right]^{T} \forall k \in Z \quad\left\{\left[\begin{array}{l}-1 \\ -1 \\ -1\end{array}\right],\left[\begin{array}{l}0 \\ 0 \\ 0\end{array}\right],\left[\begin{array}{c}-1 \\ -1 \\ 1\end{array}\right],\left[\begin{array}{c}0 \\ -2 \\ 0\end{array}\right]\right\}$
calnvariant set of weights of the perceptron: $\wp=\left\{\left[\begin{array}{lll}-1, & -1, & -1\end{array}\right]^{\Gamma}\right\}$ calnvariant map: $\mathfrak{I}^{F}:\left\{\left[\begin{array}{lll}-1, & -1, & -1\end{array}\right]^{T}\right\} \rightarrow\left\{\left[\begin{array}{ll}-1, & -1, \\ \hline\end{array}\right]^{T}\right\}$
c Note: $\tilde{\mathfrak{J}}^{F}: \mathfrak{R}^{3} \rightarrow \mathfrak{R}^{3}$ is not bijective because $\|\mathbf{x}(k)\|^{2}>\left|\mathbf{w}^{T}(k) \mathbf{x}(k)\right|$ $\forall k \in Z$


## Perceptron training algorithms






## Perceptron training algorithms

* Example 5

\& Desirable output $\{1,-1,1,-1\}$
© Initial weight $\mathbf{w}(0)=\left[\begin{array}{lll}-1, & 0.7923, & -0.2133\end{array}\right]^{T}$
cllnvariant set of the weights of the perceptron consists of three hyperplanes.
$\propto$ Note: $\tilde{\mathfrak{J}}^{F}: \mathfrak{R}^{3} \rightarrow \mathfrak{R}^{3}$ is not bijective because $\exists k \in Z$

$$
\|\mathbf{x}(k)\|^{2}>\left|\mathbf{w}^{T}(k) \mathbf{x}(k)\right|
$$

## Perceptron training algorithms



## Conclusions

*Many digital signal processing systems are symbolic dynamical systems.

* These symbolic dynamical systems could exhibit fractal, chaotic and divergent behaviors.
*By investigating the properties of these symbolic dynamical systems, unwanted behaviors could be avoided.


