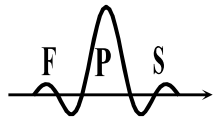


# Summary

- *Sampling and reconstruction of continuous signals*
  - *Introduction*
  - *Periodic sampling of continuous-time signals*
  - *Frequency domain analysis of periodic sampling*
  - *Reconstruction of continuous-time signals from samples*
    - *Ideal reconstruction*
    - *Zero-order real reconstruction*
  - *Discrete-time processing of continuous-time signals*



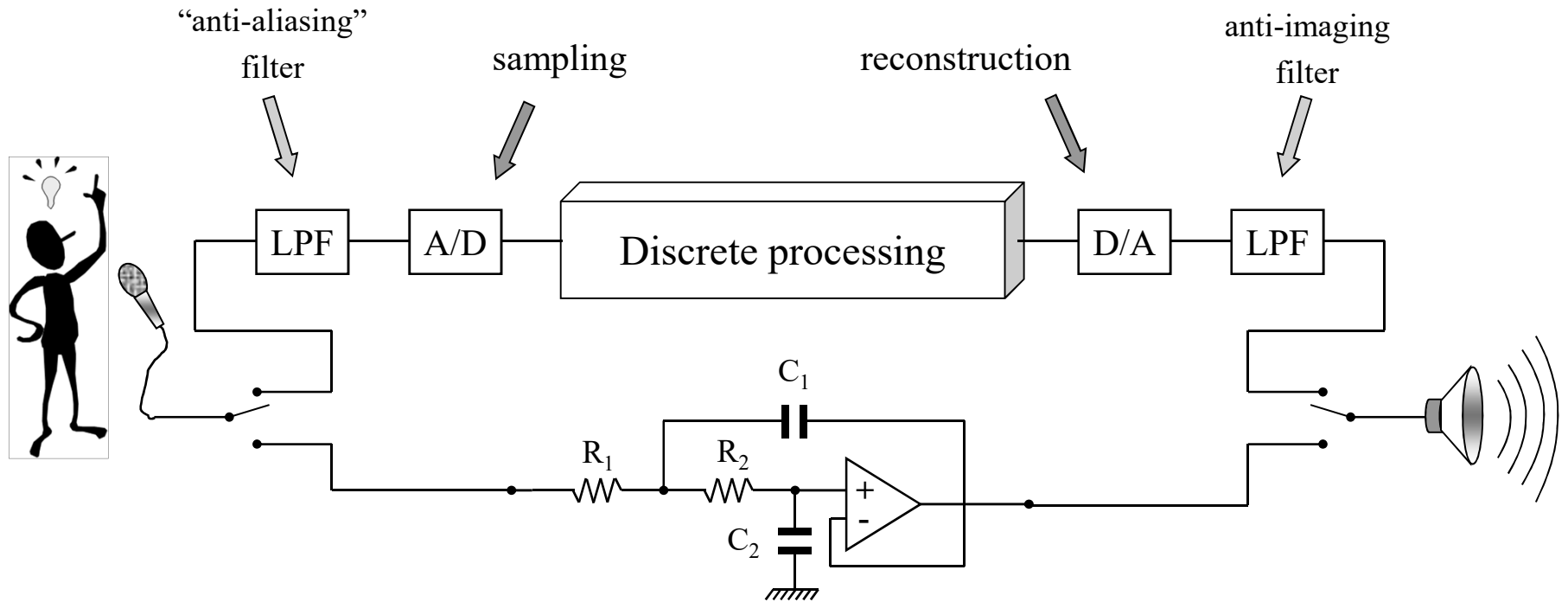
# Sampling of continuous-time signals

- Introduction
  - most discrete-time signals result from sampling (*i.e.* discretization in time) of continuous-time signals
  - under certain conditions, a discrete-time signal may be an exact representation (*i.e.* there is no loss of information) of a continuous-time signal
  - any form of processing of a continuous-time signal may be realized in the discrete domain, which requires the sampling of the continuous-time signal before processing, and the reconstruction of the continuous-time signal from samples after the processing stage

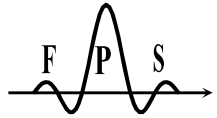


# Sampling of continuous-time signals

- Introduction (cont.)
  - is discrete-time processing preferable to analog processing ?

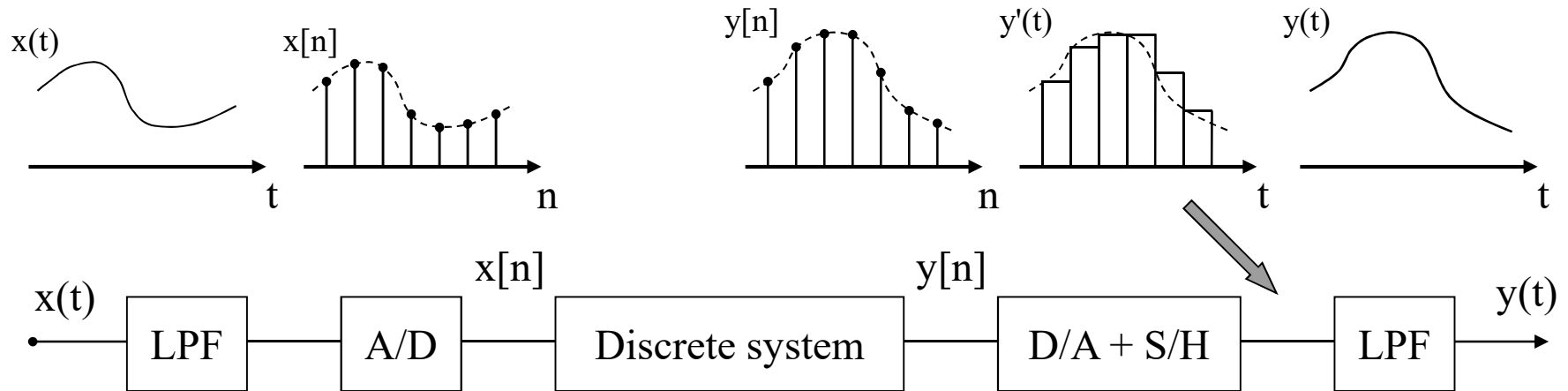


- e.g. is there any non-trivial analog filter with exact linear phase ? (but easy to realize using a discrete-time system...)

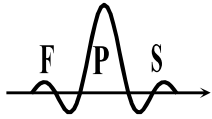


# Sampling of continuous-time signals

- Context
  - minimal structure for the discrete-time processing of analog signals:



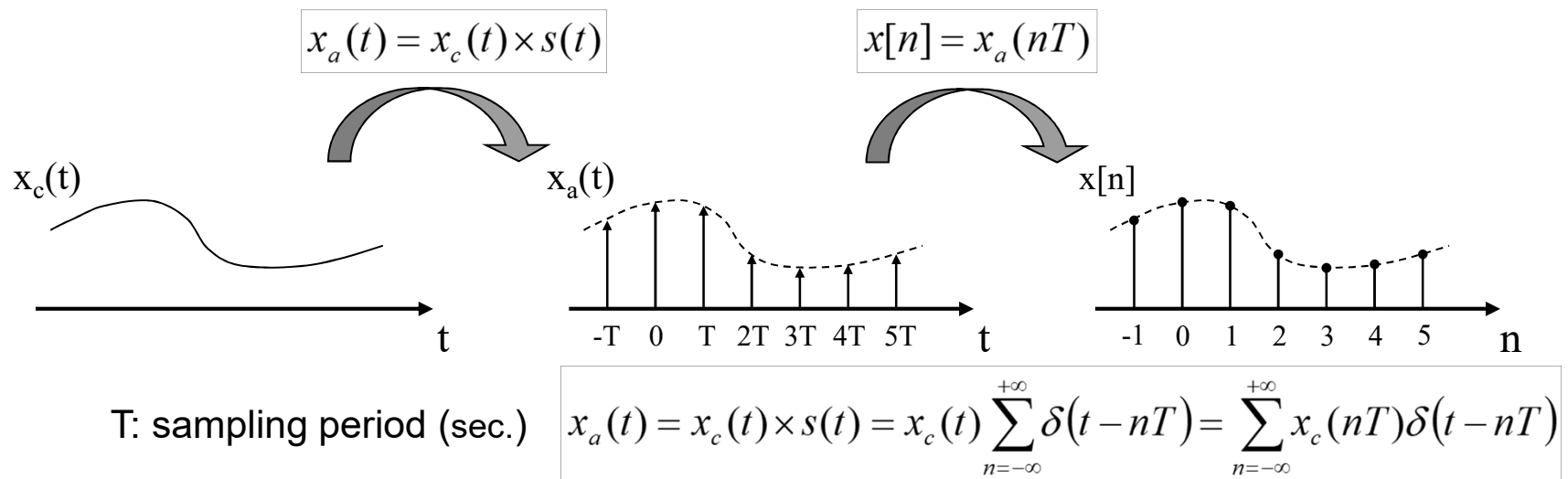
- in the following we admit that the sampling rate is constant and that the A/D and D/A converters have infinite resolution (i.e., no quantization errors)
- QUESTION: in the absence of discrete-time processing, i.e., if  $y[n]=x[n]$ , and admitting ideal A/D and D/A converters, under which conditions is it possible to sample and reconstruct an analog signal without loss of information, i.e., such that  $y(t)=x(t)$  ?



# Sampling of continuous-time signals

- in order to answer the previous question, we analyze two fundamental steps in the represented block diagram : the time discretization of the continuous-time signal by means of a periodic sampling (continuous-time signal  $\rightarrow$  discrete-time signal conversion) and the time reconstruction of the continuous-time signal from samples (discrete-time signal  $\rightarrow$  continuous-time signal conversion)

- periodic sampling



T: sampling period (sec.)

$$x_a(t) = x_c(t) \times s(t) = x_c(t) \sum_{n=-\infty}^{+\infty} \delta(t - nT) = \sum_{n=-\infty}^{+\infty} x_c(nT) \delta(t - nT)$$

1/T: sampling frequency (Hertz)

$\Omega_s = 2\pi/T$ : angular sampling frequency (radians/seg.)

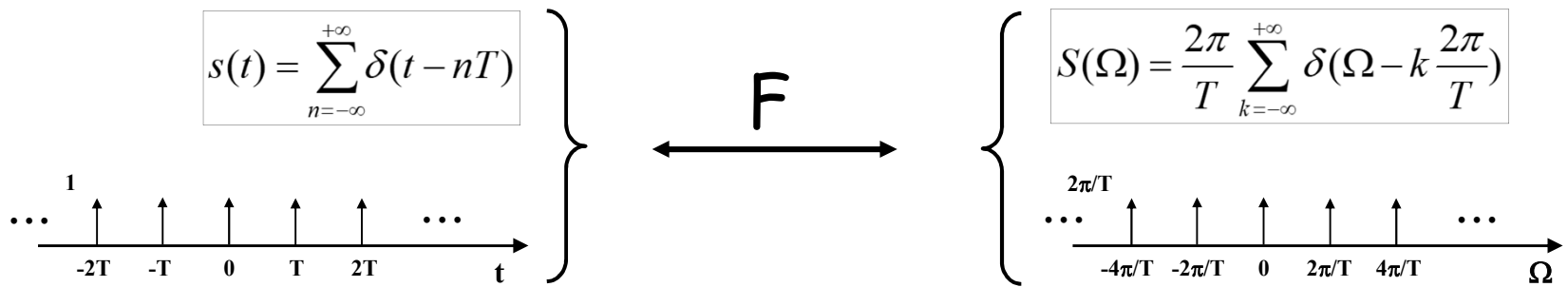
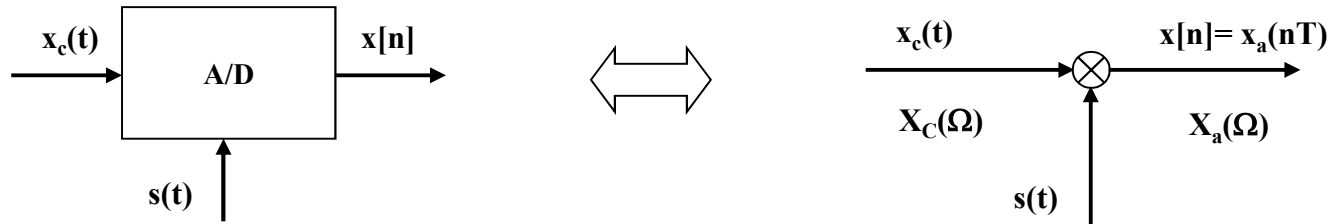
$$x[n] = x_a(nT) \quad , \quad -\infty < n < +\infty$$

- NOTE: this operation is only invertible (*i.e.*, the ambiguity is avoided of two different signals giving rise to the same discrete signal) if  $x_c(t)$  is constrained.



# Frequency domain analysis of periodic sampling

– time discretization: how to relate  $X(e^{j\omega})$  and  $X_c(\Omega)$  ?

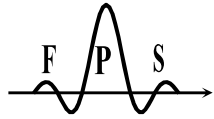


$$x_a(t) = x_c(t) \cdot s(t) = \sum_{n=-\infty}^{+\infty} x_c(nT) \delta(t - nT) \quad \xleftrightarrow{F} \quad X_a(\Omega) = \frac{1}{2\pi} X_c(\Omega) * S(\Omega) = \frac{1}{T} \sum_{k=-\infty}^{+\infty} X_c\left(\Omega - k \frac{2\pi}{T}\right)$$

and also:

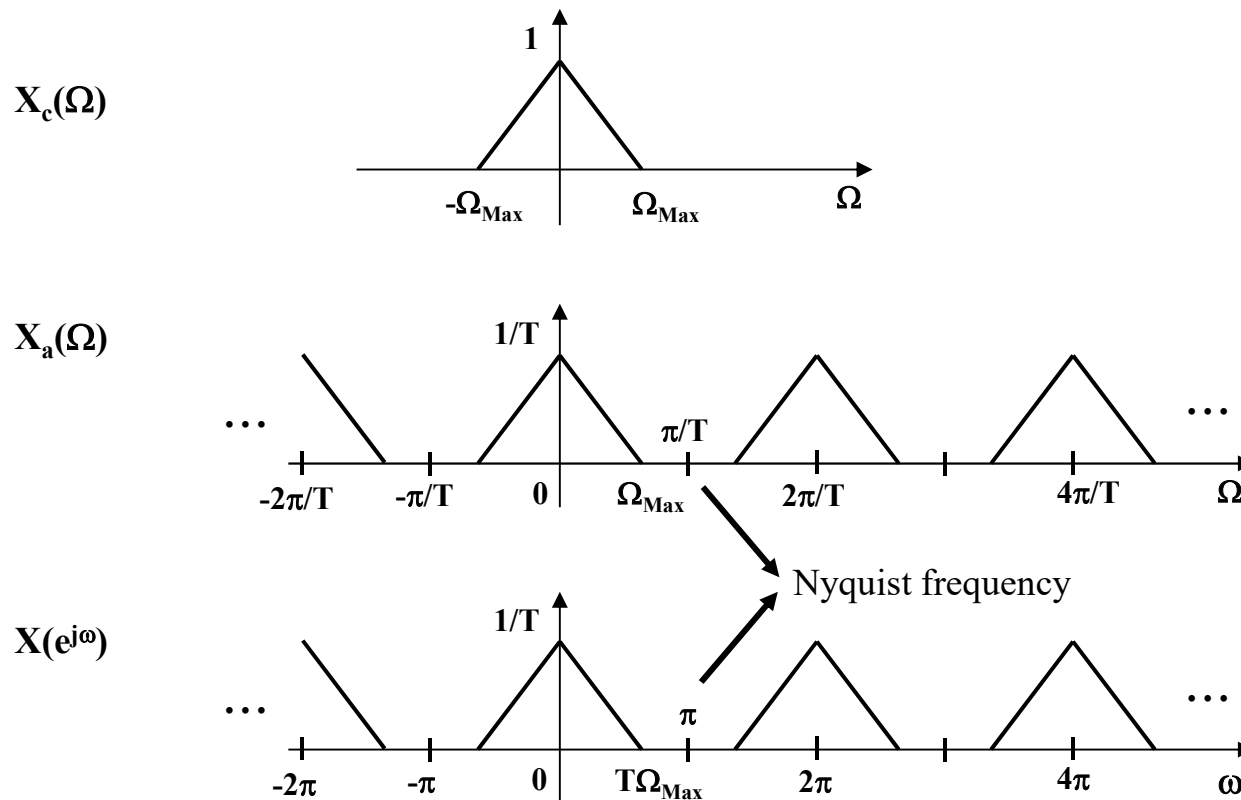
$$x_a(t) = \sum_{n=-\infty}^{+\infty} x_c(nT) \delta(t - nT) \quad \xleftrightarrow{F} \quad X_a(\Omega) = \sum_{n=-\infty}^{+\infty} x_c(nT) e^{-jn\Omega T} \Big|_{\substack{x[n]=x_c(nT) \\ \omega=\Omega T}} = \sum_{n=-\infty}^{+\infty} x[n] e^{-jn\omega} = X(e^{j\omega})$$

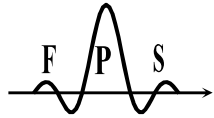
thus: 
$$X(e^{j\omega}) = X_a(\Omega) \Big|_{\Omega=\frac{\omega}{T}} = \frac{1}{T} \sum_{k=-\infty}^{+\infty} X_c\left(\frac{\omega - k2\pi}{T}\right)$$



# Frequency domain analysis of periodic sampling

→ The previous result says that except for a scale factor and a normalization (by  $1/T$ ) of the frequency axis (making that the “analog” frequency  $k2\pi/T = k\Omega_s$  be projected in the “digital” frequency  $k2\pi$ , for any integer  $K$ ) the spectra  $X(e^{j\omega})$  and  $X_a(\Omega)$  are similar. It also says that, as result of ideal sampling, the spectrum of the continuous-time signal appears replicated at all multiple integers of the sampling frequency.





# Frequency domain analysis of periodic sampling

## The Nyquist sampling theorem

- in order to avoid spectral overlap (i.e., *aliasing*) between replicas of the base-band spectrum, it must be ensured that :

$$\Omega_{\text{MAX}} < \pi/T = \Omega_S/2 \Leftrightarrow 2\pi F_{\text{MAX}} < \pi F_S \Leftrightarrow F_S > 2F_{\text{MAX}}$$

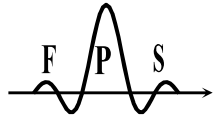
- this means that the bandwidth of the base-band signal must be limited to less than half the sampling frequency. This condition is typically enforced by a low-pass filter just before the A/D converter, thus named “anti-aliasing” filter.
- if this condition is guaranteed, as the illustration suggests, it is possible to recover  $X_c(\Omega)$  from  $X(e^{j\omega})$ , using an ideal low-pass continuous-time filter, with gain  $T$  and cut-off frequency  $\Omega_{\text{MAX}} < \Omega_p < \Omega_S - \Omega_{\text{MAX}}$

these aspects reflect the Nyquist sampling theorem:

- is  $x_c(t)$  is a band-limited signal such that  $X_c(\Omega) = 0$  for  $|\Omega| > \Omega_{\text{MAX}}$ , then  $x_c(t)$  is uniquely determined (i.e. may be unambiguously reconstructed) from its samples  $x[n] = x_c(nT)$  with  $\Omega_S = 2\pi/T > 2\Omega_{\text{MAX}}$

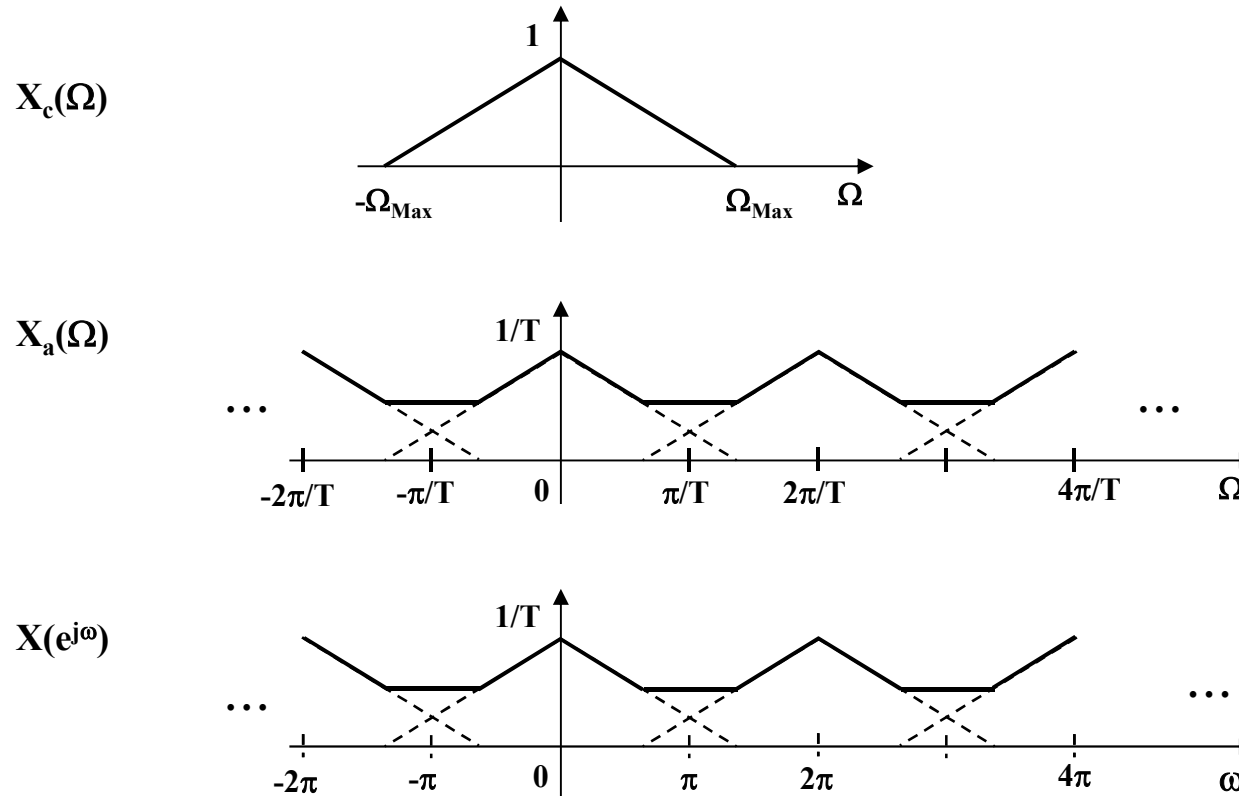
NOTE:  $\Omega_S/2 = \pi/T$  is commonly known as the Nyquist frequency.



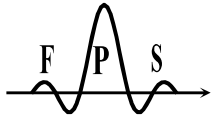


# Frequency domain analysis of periodic sampling

→ what if the sampling condition is violated, i.e., if  $F_S < 2F_{MAX}$  ?



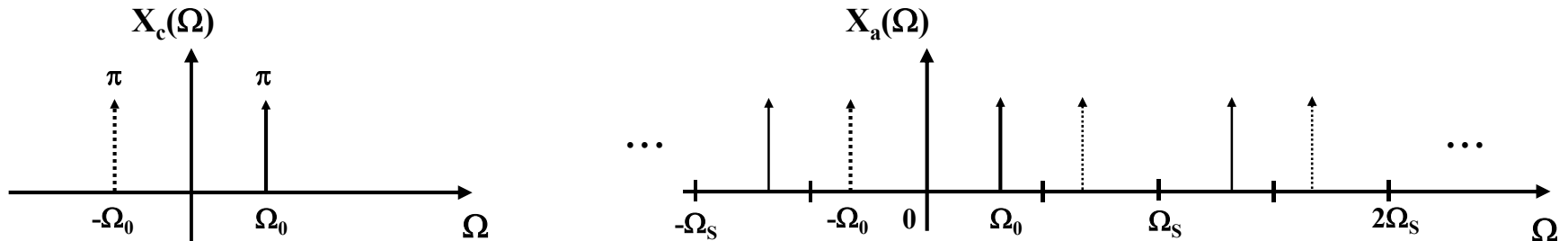
**Answer:** there is spectral overlap ( “aliasing” ) distorting the signal, and preventing the recovery of the original spectrum after low-pass filtering.



# Frequency domain analysis of periodic sampling

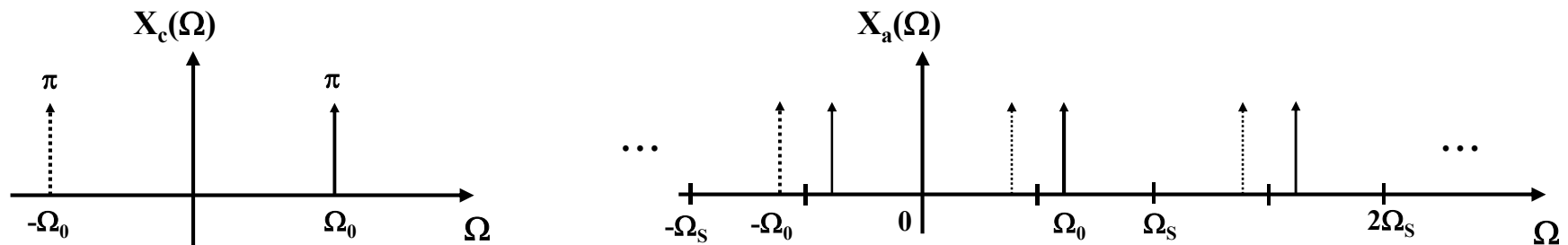
example: case of a continuous-time signal (co-sinusoidal function) correctly and incorrectly sampled

$x_c(t) = \cos(\Omega_0 t)$  ,  $\Omega_0 < \Omega_s/2$   $\therefore$  there is no “aliasing”

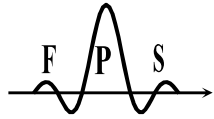


recovered signal after low-pass filtering, with cut-off at  $\Omega_s/2$  :  $x_c(t) = \cos(\Omega_0 t)$

$x_c(t) = \cos(\Omega_0 t)$  ,  $\Omega_0 > \Omega_s/2$   $\therefore$  there is “aliasing”

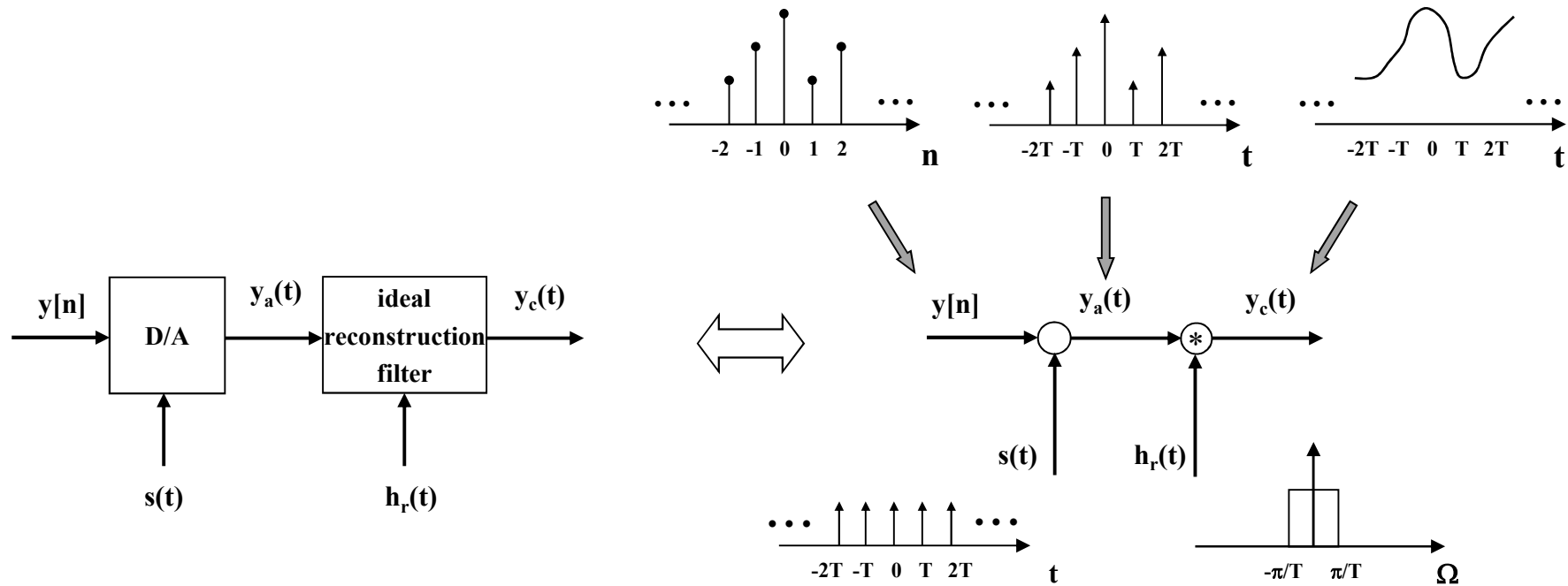


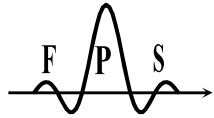
recovered signal after low-pass filtering, with cut-off at  $\Omega_s/2$  :  $x_c(t) = \cos[(\Omega_s - \Omega_0)t]$



# Reconstruction from samples

- Case 1: ideal reconstruction
  - as can be concluded from the spectral representation of  $X_a(\Omega)$  ('slide' n° 7), if we preserve solely the base-band replica after low-pass filtering, then it is possible to recover the spectrum  $X_c(\Omega)$ ; the same is to say: it is possible to recover  $x_c(t)$ . This is the principle which we will illustrate next using  $y[n]$ .



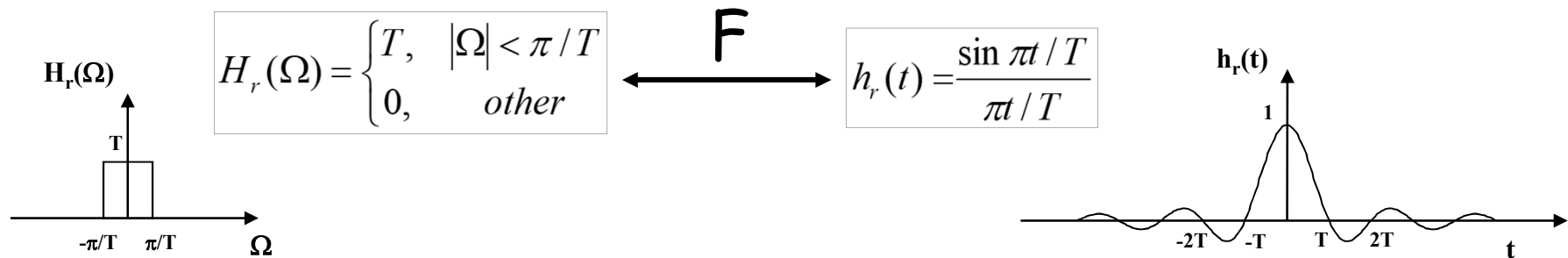


# Reconstruction from samples

The first step going from the discrete-time domain to the continuous-time domain involves placing the pulses of the discrete sequence  $y[n]$  at instants uniformly distributed in time, thus obtaining  $y_a(t)$ . It should be noted that this signal has the same spectrum of  $x_a(t)$  since we presume that  $y[n]=x[n]$ .

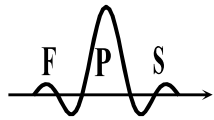
$$y_a(t) = \sum_{n=-\infty}^{+\infty} y[n]\delta(t - nT) \xleftrightarrow{\mathbf{F}} Y_a(\Omega) = \sum_{n=-\infty}^{+\infty} y_a(nT)e^{-jn\Omega T} \Big|_{\substack{y(n)=y_a(nT) \\ \omega=\Omega T}} = \sum_{n=-\infty}^{+\infty} y[n]e^{-jn\Omega T} = Y(e^{j\Omega T})$$

By submitting the continuous-time signal  $y_a(t)$  to an ideal low-pass filter having impulse response  $h_r(t)$ , gain  $T$  and cutting-off frequency at  $\pi/T$ :



we obtain:

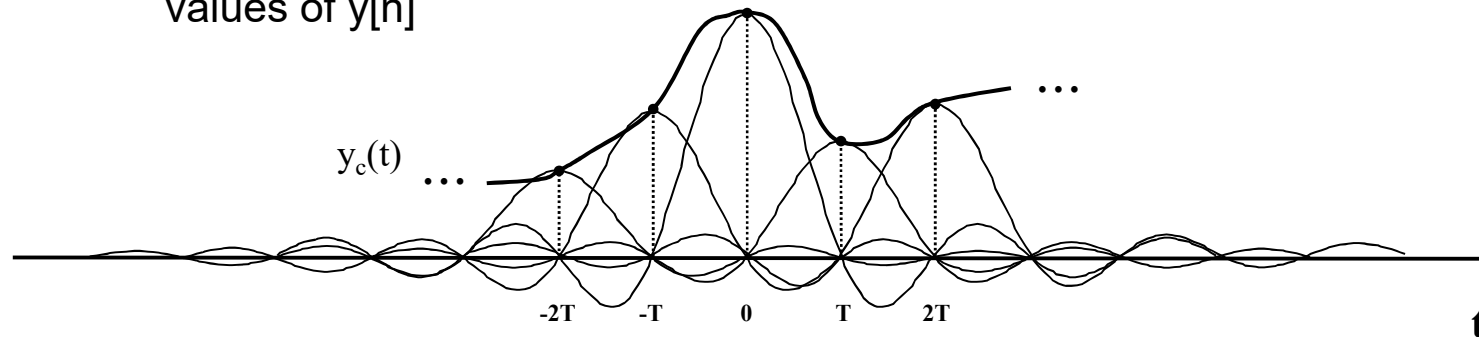
$$y_c(t) = y_a(t) * h_r(t) = \sum_{n=-\infty}^{\infty} y_a(nT) \frac{\sin \pi(t - nT)/T}{\pi(t - nT)/T} = \sum_{n=-\infty}^{\infty} y[n] \operatorname{sinc} \frac{\pi}{T}(t - nT)$$



# Reconstruction from samples

This result reveals that:

- at the sampling instants  $y_c(nT)=y[n]=x[n]=x_c(nT)$ , given that all sinc functions in the summation are zero, except one (that centered at  $t=nT$ ) whose value is 'one',
- at intermediary instants, the continuous-time signal results from the sum of all sinc functions, i.e. the filter  $h_r(t)$  implements an interpolation using all values of  $y[n]$



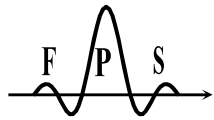
using frequency-domain analysis, and considering  $y[n]=x[n]$  which implies:

$$Y_a(\Omega) = Y(e^{j\omega}) \Big|_{\omega=\Omega T} = X(e^{j\omega}) \Big|_{\omega=\Omega T} = X_a(\Omega)$$

It can be concluded that the result of filtering is:

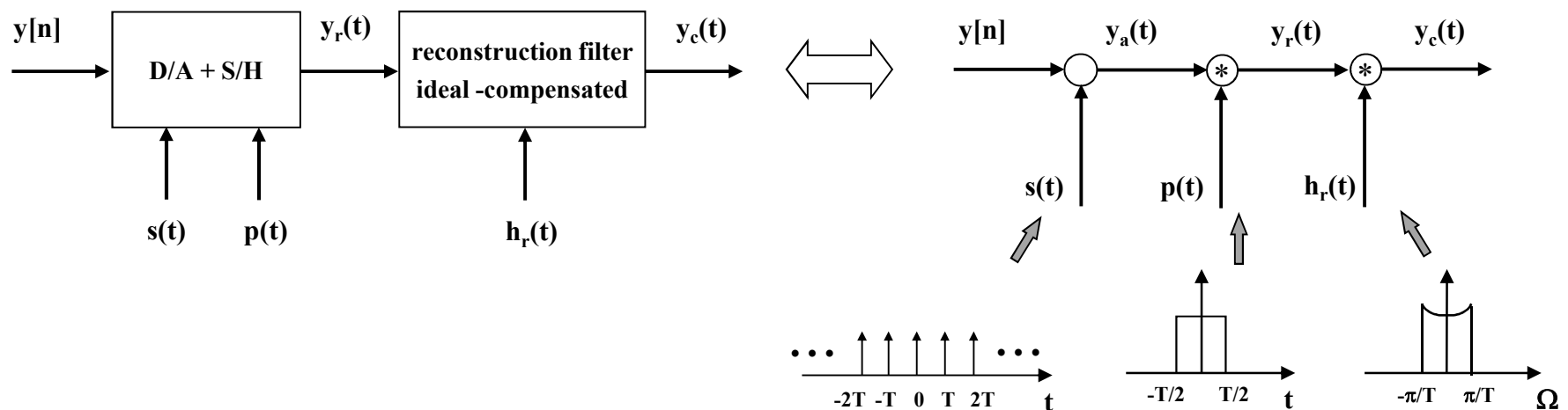
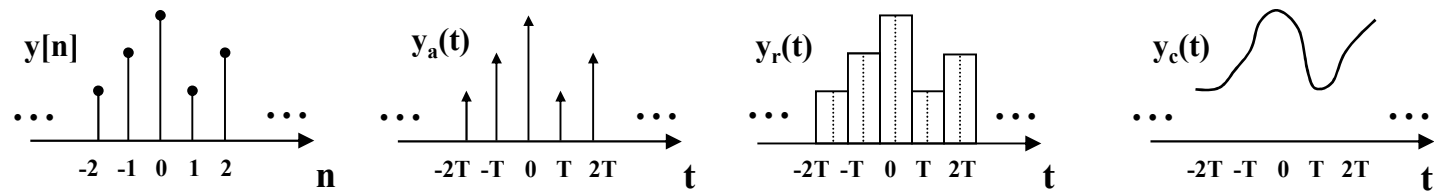
$$y_c(t) = y_a(t) * h_r(t) \quad \xleftrightarrow{\text{F}} \quad Y_c(\Omega) = X_a(\Omega) \cdot H_r(\Omega) = \frac{1}{T} \sum_{k=-\infty}^{+\infty} X_c\left(\Omega - k \frac{2\pi}{T}\right) H_r(\Omega) = X_c(\Omega)$$

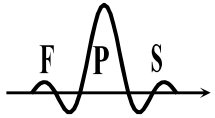
which means that, considering ideal conditions and the Nyquist criterion, it is possible to reconstruct the continuous-time signal from its samples, without loss of information. **Question:** the reconstruction filter is also known as anti-imaging filter, why ?



# Reconstruction from samples

- Case 2: zero-order real reconstruction
  - real electronic devices, in particular D/A converters, do not operate using pulses but use instead more physically tractable signals such as boxcar function approximations. Let us consider the case closest to reality where the D/A converter is associated with a “sample-and-hold” device that ‘retains’ the value of a sample during a sampling period, giving rise to a staircase-like signal:





# Reconstruction from samples

as considered before:

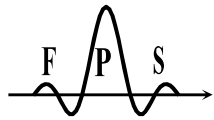
$$y_a(t) = \sum_{n=-\infty}^{+\infty} y[n]\delta(t - nT) \xleftrightarrow{F} Y_a(\Omega) = Y(e^{j\omega}) \Big|_{\omega=\Omega T} = Y(e^{j\Omega T})$$

and for the boxcar function of width T:

$$p(t) = \begin{cases} 1, & |t| < T/2 \\ 0, & \text{outros} \end{cases} \xleftrightarrow{F} P(\Omega) = T \frac{\sin \Omega T / 2}{\Omega T / 2}$$

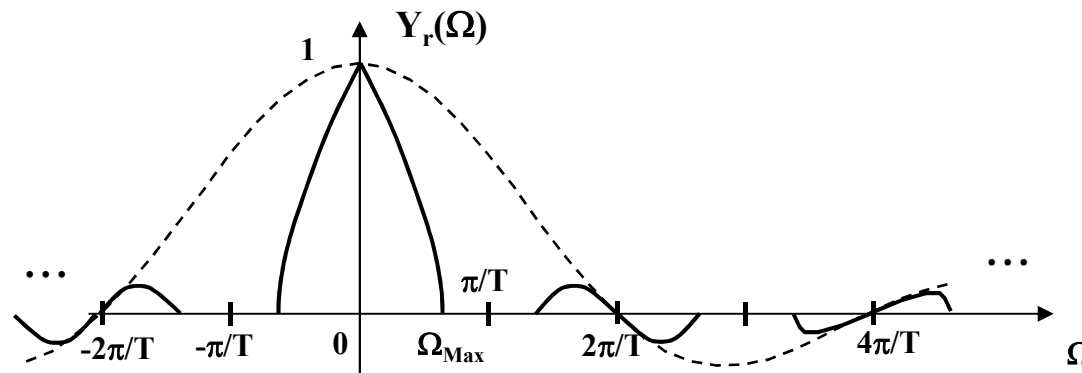
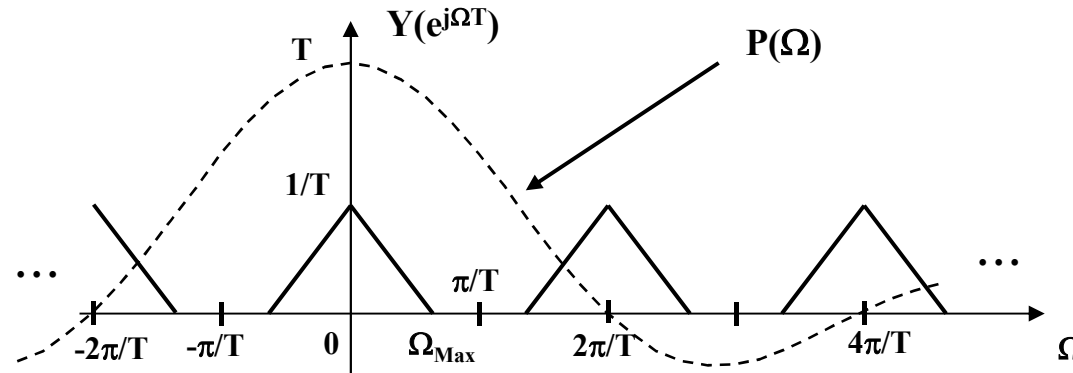
and therefore  $y_r(t)$  results as:

$$y_r(t) = y_a(t) * p(t) = \sum_{n=-\infty}^{+\infty} y[n]p(t - nT) \xleftrightarrow{F} Y_r(\Omega) = Y(e^{j\Omega T}) T \frac{\sin \Omega T / 2}{\Omega T / 2}$$



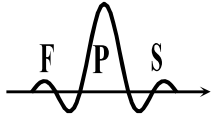
# Reconstruction from samples

whose spectral representation is:



from where it can be concluded that the zero-order reconstruction distorts the  $Y(e^{j\Omega T})$  spectrum in a way that can be compensated for, if we consider the base-band replica which is the one we want to recover; in addition, all other replicas which we want to eliminate, are strongly attenuated which alleviates the filtering effort of  $h_r(t)$ .





# Reconstruction from samples

The filter  $h_r(t)$  must then not only reject the undesirable spectral images, but also compensate the magnitude distortion affecting the base-band replica :

$$y_c(t) = y_r(t) * h_r(t) \xleftrightarrow{F} Y_c(\Omega) = Y_r(\Omega) \cdot H_r(\Omega) = Y(e^{j\Omega T}) T \cdot \frac{\sin \Omega T / 2}{\Omega T / 2} \cdot H_r(\Omega)$$

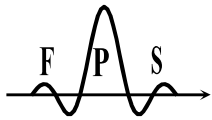
presuming also that  $y[n]=x[n]$ , then:  $Y(e^{j\omega}) \Big|_{\omega=\Omega T} = X(e^{j\omega}) \Big|_{\omega=\Omega T} = X_a(\Omega)$

$$Y_c(\Omega) = X_a(\Omega) \cdot T \frac{\sin \Omega T / 2}{\Omega T / 2} \cdot H_r(\Omega) = \sum_{k=-\infty}^{+\infty} X_c(\Omega - k \frac{2\pi}{T}) \cdot \frac{\sin \Omega T / 2}{\Omega T / 2} \cdot H_r(\Omega) = X_c(\Omega)$$



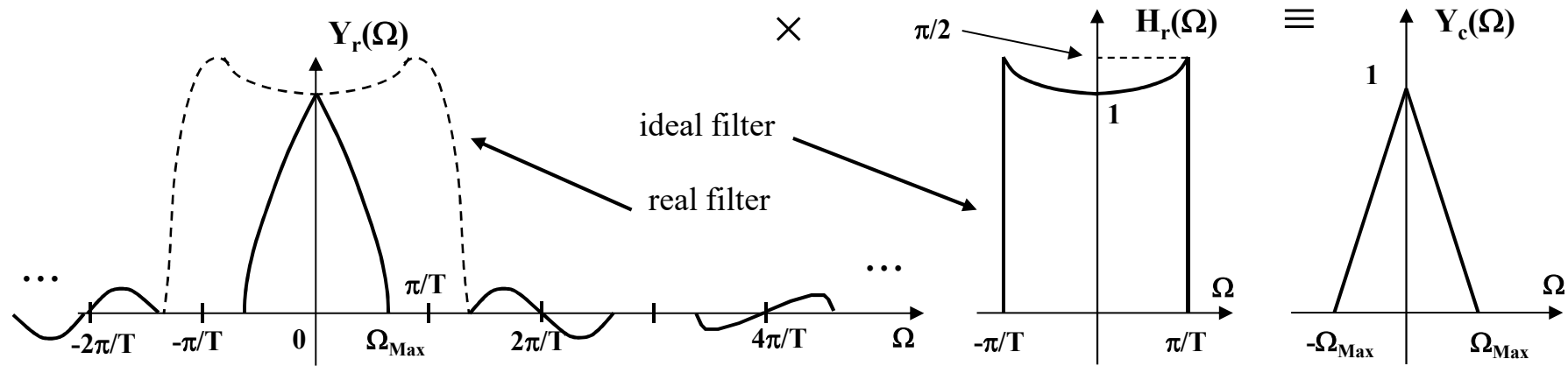
subject to the condition that filter  $H_r(\Omega)$  is low-pass, with cut-off frequency at  $\pi/T$ , but is also compensated such as to reverse the  $\sin(x)/x$  distortion, i.e. :

$$H_r(\Omega) = \begin{cases} \frac{\Omega T / 2}{\sin \Omega T / 2}, & |\Omega| < \pi / T \\ 0, & \text{other} \end{cases}$$



# Reconstruction from samples

Then, it results graphically:

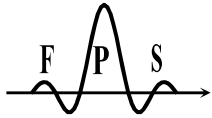


which means the output of  $h_r(t)$  is also given by:  
as we have already concluded before.

$$y_c(t) = \sum_{n=-\infty}^{\infty} x_c(nT) \frac{\sin \pi(t - nT)/T}{\pi(t - nT)/T}$$

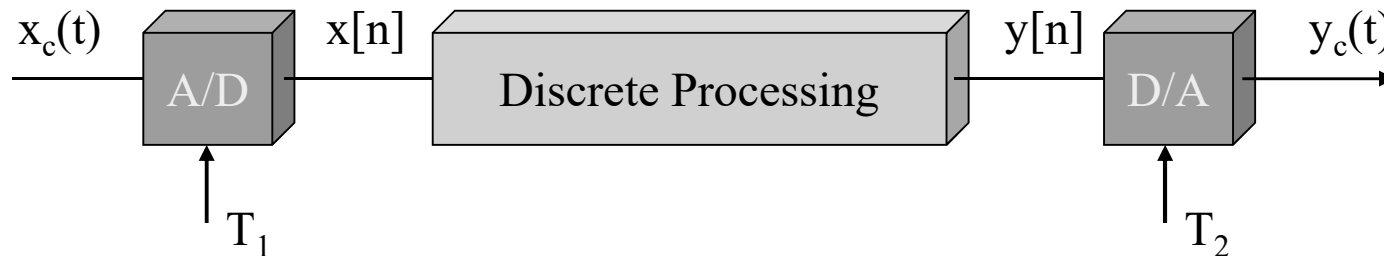
NOTE 1: the compensation  $\sin(x)/x$  may be inserted at any stage of the processing, including (and perhaps preferably ! ) at the discrete processing stage, with all the known advantages.

NOTE 2: in addition to the 'zero-order' reconstruction, there are other possibilities (e.g. the 'one-order' reconstruction) !

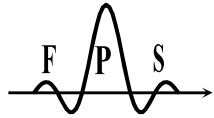


## Discrete-time processing of continuous-time signals

- In our previous analysis we have admitted  $y[n]=x[n]$ , i.e., absence of discrete-time processing so as to show the possibility of sampling and reconstruction an analog signal. It is important to assess now the impact on the analog signal of a discrete-time processing as this is the most common scenario:



- Although it is possible/desirable to design systems where the A/D sampling frequency is different from the D/A sampling frequency, (e.g. that is the case of oversampling that is used in CD/MP3 players), we admit in this analysis that both are equal.



## Discrete-time processing of continuous-time signals

- If the discrete-time system is LTI and is characterized in the frequency by  $H(e^{j\omega})$ , then:  $Y(e^{j\omega}) = H(e^{j\omega})X(e^{j\omega})$

but since:  $X(e^{j\omega}) = X_a(\Omega)|_{\Omega=\omega/T}$  which means:  $X(e^{j\Omega T}) = X_a(\Omega) = \frac{1}{T} \sum_{k=-\infty}^{+\infty} X_c\left(\Omega - k \frac{2\pi}{T}\right)$

We have also seen that considering for example zero-order reconstruction, then:

$$Y_c(\Omega) = Y(e^{j\Omega T}) T \frac{\sin \Omega T / 2}{\Omega T / 2} H_r(\Omega)$$

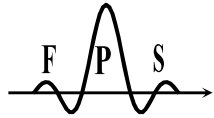
and we obtain finally:

$$Y_c(\Omega) = H(e^{j\Omega T}) \cdot \frac{\sin \Omega T / 2}{\Omega T / 2} \cdot H_r(\Omega) \sum_{k=-\infty}^{+\infty} X_c\left(\Omega - k \frac{2\pi}{T}\right)$$

we may thus conclude that:

- if the ‘anti-aliasing’ filter at the input of the system enforces  $X_c(\Omega)=0$  for  $|\Omega| > \pi/T$  (or if  $x_c(t)$  possesses already this property), then there is no overlap of spectral images in the summation
- if the reconstruction filter eliminates spectral images for  $|\Omega| > \pi/T$  and ensures  $\sin(x)/x$  compensation, then the previous expression simplifies to:

$$Y_c(\Omega) = H(e^{j\Omega T}) X_c(\Omega) = H_{eff}(\Omega) X_c(\Omega)$$



## Discrete-time processing of continuous-time signals

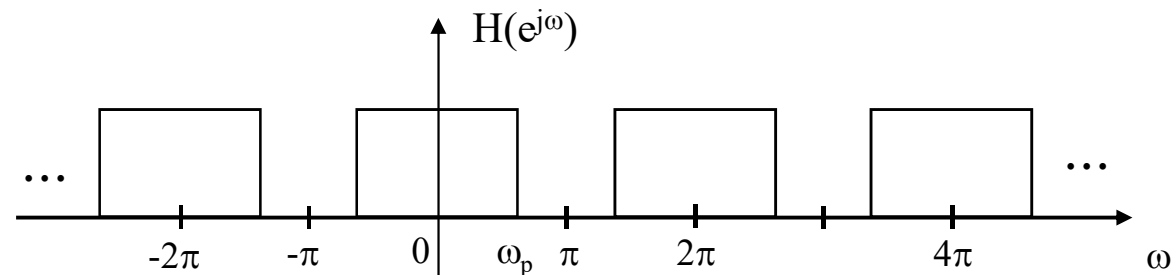
- we may finally conclude that if the discrete-time system is linear and time-invariant, from the input to the output of the system all happens as if there is an analog processing characterized by  $H_{\text{eff}}(\Omega)$ , whose relation to discrete-time processing is:

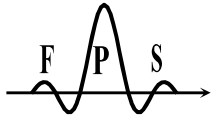
$$H_{\text{eff}}(\Omega) = \begin{cases} H(e^{j\Omega T}), & |\Omega| < \pi / T \\ 0, & |\Omega| \geq \pi / T \end{cases}$$

Example: continuous-time low-pass filtering by means of a discrete-time filter

given the filter:  $H(e^{j\omega}) = \begin{cases} 1, & |\omega| < \omega_p \\ 0, & \omega_p < |\omega| \leq \pi \end{cases}$  whose frequency response is

$\omega$ -periodic, with period  $2\pi$  :

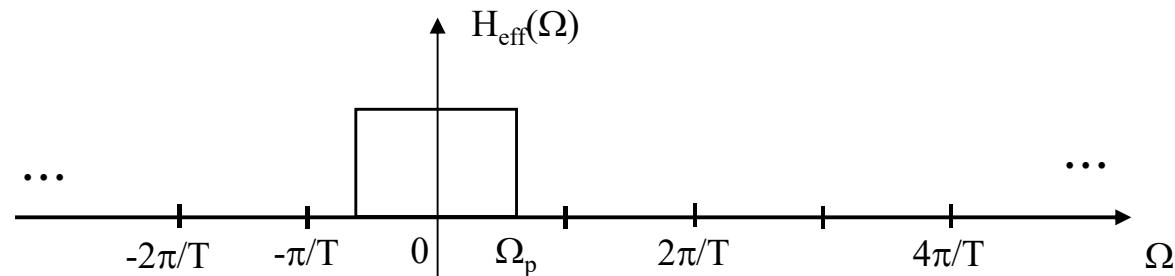




## Discrete-time processing of continuous-time signals

then:

$$H_{eff}(\Omega) = \begin{cases} 1, & |\Omega T| < \omega_p \\ 0, & |\Omega T| > \omega_p \end{cases} = \begin{cases} 1, & |\Omega| < \Omega_p = \omega_p / T \\ 0, & |\Omega| > \Omega_p = \omega_p / T \end{cases}$$



A few reasons justifying that this analog filter implemented in the discrete-time domain may be preferable:

- as the cut-off frequency  $\Omega_p = \omega_p / T$  depends on  $T$ , using the same system, we may vary the effective analog cut-off frequency (i.e., we have adjustable filters), by acting solely on the sampling frequency ( $1/T$ ),
- when we need a filter with demanding specifications, involving for example very narrow transition bands, or high stop-band attenuation, or many bands with different gains and attenuations; its realization in the analog domain is difficult, probably very expensive, and highly dependent on the characteristics of the analog components, and in any case it will show a strongly non-linear phase response. Moving that filtering effort to the discrete-time domain eliminates almost completely these inconveniences. A specific case where that is true involves A/D and D/A operations, that require, respectively, “anti-aliasing” and “anti-imaging” filters, both low-pass. The analog filter specifications are ‘alleviated’ (and in certain cases no analog filtering at all is needed) transferring most of the filtering effort to the discrete/digital domain although requiring a significant increase of the sampling frequency. In the first case, (i.e. after A/D conversion), decimating digital filters are used and in the second case (i.e. before D/A conversion), interpolating digital filters are used. We will return to these topics later on !