

IB Paper 7. Mathematical Methods (1996)

Q1
i) Volume, $V = \iint_{R'} z \, dx \, dy = \iint_R xy \, dx \, dy$

In 2D cartesian to polar transformation

$$\begin{aligned}x &= r \cos \theta \\y &= r \sin \theta\end{aligned}$$

The Jacobian of the transformation, $J = \begin{vmatrix} \cos \theta & \sin \theta \\ -r \sin \theta & r \cos \theta \end{vmatrix}$
($dx \, dy \rightarrow |J| \, dr \, d\theta$)

= r

$$V = \iint_{R'} xy \, dx \, dy = \iint_R r^2 \cos \theta \sin \theta |J| \, dr \, d\theta$$

$$= \iint_R r^3 \cos \theta \sin \theta \, dr \, d\theta$$

ii. Region of integration

$$R': y=0, y=x, (x-a)^2 + y^2 = a^2$$

$$R: \theta=0 \text{ to } \theta = \frac{\pi}{4}$$

$$(r \cos \theta - a)^2 + (r \sin \theta)^2 = a^2 \implies r^2 - 2ar \cos \theta = 0$$
$$r(r - 2a \cos \theta) = 0$$

$$r=0 \text{ to } r = 2a \cos \theta$$

$$\therefore \text{Volume, } V = \int_0^{\frac{\pi}{4}} \int_0^{2a \cos \theta} r^3 \cos \theta \sin \theta \, dr \, d\theta$$

$$= \int_0^{\frac{\pi}{4}} \cos \theta \sin \theta \int_0^{2a \cos \theta} r^3 \, dr$$

$$= \int_0^{\frac{\pi}{4}} \sin \theta \cos \theta \left(\frac{2a \cos \theta}{4} \right)^4 \, d\theta$$

$$= 4a^4 \int_0^{\frac{\pi}{4}} \sin \theta \cos^5 \theta \, d\theta$$

$$= 4a^4 \left[-\frac{\cos^6 \theta}{6} \right]_0^{\frac{\pi}{4}}$$

$$= \frac{4a^4}{6} \left[1 - \left(\frac{1}{\sqrt{2}} \right)^6 \right]$$

$$\underline{\underline{V = \frac{7a^4}{12}}}$$

2
a). A vector field $\underline{u}(\underline{r})$ is:

i) solenoidal if $\boxed{\nabla \cdot \underline{u} = 0}$ everywhere.
i.e. $\exists \underline{A}$ such that $\underline{u} = \nabla \times \underline{A}$

ii) irrotational if $\boxed{\nabla \times \underline{u} = 0}$ everywhere.
i.e. $\exists \phi$ such that $\underline{u} = \nabla \phi$

iii) conservative if the line integral $\int_A^B \underline{u} \cdot d\underline{r}$ is

independent of the path of integration

i.e. $\exists \phi$ such that $\underline{u} = \nabla \phi$ since $\int_A^B \underline{u} \cdot d\underline{r} = \int_A^B d\phi = \phi_B - \phi_A$

and $\oint_C \underline{u} \cdot d\underline{r} = 0$ for all paths C .

Note that the condition for \underline{u} to be conservative is the same as the condition for it to be irrotational since $\nabla \times \nabla \phi = 0$

Q2b.

$$\underline{v} = \underline{u} + \underline{\omega} \times \underline{r}$$

i) From data book Vector Calculus identities: (p12)

$$\begin{aligned} \nabla \times \underline{v} &= \nabla \times \underline{u} + \nabla \times (\underline{\omega} \times \underline{r}) \\ &= 0 + \underline{\omega} (\nabla \cdot \underline{r}) - \underline{r} (\nabla \cdot \underline{\omega}) + (\underline{r} \cdot \nabla) \underline{\omega} - (\underline{\omega} \cdot \nabla) \underline{r} \end{aligned}$$

$$\nabla \times \underline{v} = \underline{\omega} (\nabla \cdot \underline{r}) - (\underline{\omega} \cdot \nabla) \underline{r}$$

since $\underline{u} = \text{constant}$ and $\nabla \cdot \underline{\omega}$ and $(\underline{r} \cdot \nabla) \underline{\omega} = 0$

$$\begin{aligned} \nabla \cdot \underline{r} &= \frac{\partial x}{\partial x} + \frac{\partial y}{\partial y} + \frac{\partial z}{\partial z} = 3 \\ (\underline{\omega} \cdot \nabla) \underline{r} &= \left[\omega_x \frac{\partial}{\partial x} + \omega_y \frac{\partial}{\partial y} + \omega_z \frac{\partial}{\partial z} \right] [x \underline{i} + y \underline{j} + z \underline{k}] \\ &= \underline{\omega} \end{aligned}$$

$$\therefore \underline{\nabla \times \underline{v}} = \underline{3\omega - \omega} = \underline{2\omega}$$

$$\text{ii). } \nabla \cdot \underline{v} = \nabla \cdot \underline{u} + \nabla \cdot (\underline{\omega} \times \underline{r}) = \nabla \cdot (\underline{\omega} \times \underline{r})$$

$$\nabla \cdot (\underline{\omega} \times \underline{r}) = \underline{r} \cdot (\nabla \times \underline{\omega}) - \underline{\omega} \cdot (\nabla \times \underline{r})$$

$$\nabla \times \underline{\omega} = 0 \text{ and } \nabla \times \underline{r} = \begin{vmatrix} \underline{i} & \underline{j} & \underline{k} \\ \frac{\partial}{\partial x} & \frac{\partial}{\partial y} & \frac{\partial}{\partial z} \\ x & y & z \end{vmatrix} = 0$$

$$\therefore \underline{\nabla \cdot \underline{v}} = 0$$

Q2 c). $\phi = \frac{k}{r}$ and potential increases with proximity to origin

i) $\underline{p} = -\nabla\phi$ since force is repulsive

Using databook relation for spherical symmetry:

$$\begin{aligned}\nabla\phi &= \underline{e}_r \frac{d\phi}{dr} = -\underline{e}_r \frac{k}{r^2} \\ &= -\frac{k \underline{r}}{r^3}\end{aligned}$$

$$\therefore \underline{p} = \underline{\underline{\frac{k \underline{r}}{r^3}}}$$

ii). $\underline{\nabla} \times \underline{p} = \underline{\nabla} \times (\nabla\phi) = 0 \quad \therefore$ conservative field

$$\underline{\nabla} \cdot \underline{p} = \frac{1}{r^2} \frac{d}{dr} \left(\frac{r^2 k}{r^2} \right) = 0 \quad r > 0 \quad \therefore$$
 solenoidal field


$$\underline{\nabla}^2 \phi = \underline{\nabla} \cdot \nabla\phi = 0 \quad \text{for } r > 0$$

iii) Work done on particle

$$\begin{aligned} &= -\int_A^B \underline{p} \cdot d\underline{l} = \int_A^B + \nabla\phi \cdot d\underline{l} = +\int_A^B d\phi \\ &= +(\phi_B - \phi_A) \quad \text{and is independent of path.} \\ &= \frac{k}{6} - \frac{k}{5}\end{aligned}$$

$$\underline{\underline{W = -\frac{k}{30}}}$$

Q3. a) From databook (p12) Stokes' Theorem:

$$\iint_S (\nabla \times \underline{u}) \cdot d\underline{A} = \oint_C \underline{u} \cdot d\underline{l}$$


If we consider the surface S to be in the x - y plane with a closed boundary curve C in the plane and assume $\underline{u} = (u_x, u_y, u_z)$

$$d\underline{A} = dx dy \underline{k} \quad \text{and} \quad d\underline{l} = dx \underline{i} + dy \underline{j}$$

$$\therefore \underline{k} \cdot (\nabla \times \underline{u}) = \underline{k} \cdot \begin{vmatrix} \underline{i} & \underline{j} & \underline{k} \\ \frac{\partial}{\partial x} & \frac{\partial}{\partial y} & \frac{\partial}{\partial z} \\ u_x & u_y & u_z \end{vmatrix} = \frac{\partial u_y}{\partial x} - \frac{\partial u_x}{\partial y}$$

Thus Stokes' theorem becomes Green's Theorem in the plane:

$$\iint_S \left(\frac{\partial u_y}{\partial x} - \frac{\partial u_x}{\partial y} \right) dx dy = \oint_C u_x dx + u_y dy$$

$$\text{Let } \underline{u} = (P, Q, R) \Rightarrow \iint_S \left(\frac{\partial Q}{\partial x} - \frac{\partial P}{\partial y} \right) dx dy = \oint_C P dx + Q dy$$

3b). In general $P = P(x, y)$, $Q = Q(x, y)$

If $\frac{\partial Q}{\partial x} - \frac{\partial P}{\partial y} = 1$ then L.H.S becomes:

$$\iint_S 1 \, dx \, dy \equiv \text{area of } S \text{ enclosed by curve } C, A$$

$$i) \text{ let } P = -y/2, \quad Q = \frac{x}{2} \quad A = \oint_C \frac{-y \, dx + x \, dy}{2}$$

$$A = \frac{1}{2} \oint_C x \, dy - y \, dx$$

$$ii) \text{ let } P = 0, \quad Q = x,$$

$$A = \oint_C x \, dy$$

$$iii) \text{ let } P = -y, \quad Q = 0,$$

$$A = -\oint_C y \, dx$$

$$\therefore \text{Area of } S = \frac{1}{2} \oint_C x \, dy - y \, dx = \oint_C x \, dy = -\oint_C y \, dx$$

iv). For an ellipse $\frac{x^2}{a^2} + \frac{y^2}{b^2} = 1$ and $x = a \cos \theta$
 $y = b \sin \theta \quad dy = b \cos \theta \, d\theta$

$$\therefore \text{Area} = \oint_C x \, dy = \int_0^{2\pi} \underbrace{a \cos \theta}_x \underbrace{b \cos \theta \, d\theta}_{dy} = ab \int_0^{2\pi} \cos^2 \theta \, d\theta$$

$$\underline{\underline{A = \pi ab}}$$

Q4 Assume functions have continuous derivatives and use Taylor series expansion:

$$u_{i+1}^n = u(i\Delta x + \Delta x, n\Delta t)$$

$$a). \quad u_{i+1}^n = u_i^n + \Delta x \left. \frac{\partial u}{\partial x} \right|_{i,n} + \frac{\Delta x^2}{2!} \left. \frac{\partial^2 u}{\partial x^2} \right|_{i,n} + \frac{\Delta x^3}{3!} \left. \frac{\partial^3 u}{\partial x^3} \right|_{i,n} + O(\Delta x^4)$$

$$u_{i-1}^n = u_i^n - \Delta x \left. \frac{\partial u}{\partial x} \right|_{i,n} + \frac{\Delta x^2}{2!} \left. \frac{\partial^2 u}{\partial x^2} \right|_{i,n} - \frac{\Delta x^3}{3!} \left. \frac{\partial^3 u}{\partial x^3} \right|_{i,n} + O(\Delta x^4)$$

$$i). \quad \frac{u_{i+1}^n - u_{i-1}^n}{\Delta x} = \frac{\partial u}{\partial x} + \frac{\Delta x^2}{3} \frac{\partial^3 u}{\partial x^3} + O(\Delta x^3)$$

$$= \frac{\partial u}{\partial x} + O(\Delta x^2)$$

ie. the finite difference expression is consistent with $\frac{\partial u}{\partial x}$ and is second-order accurate since the leading truncation error term is $O(\Delta x^2)$. Centrod finite difference.

$$ii). \quad \frac{u_i^{n+1} - u_i^n}{\Delta t} = \frac{\partial u}{\partial t} + \frac{1}{2} \frac{\partial^2 u}{\partial t^2} \Delta t + \dots$$

$$= \frac{\partial u}{\partial t} + O(\Delta t)$$

ie. consistent with $\frac{\partial u}{\partial t}$ and is first-order accurate since leading truncation error term is $O(\Delta t)$. One-sided finite difference.

$$b). \quad \frac{u_{i+1}^n - 2u_i^n + u_{i-1}^n}{\Delta x^2} = \frac{\partial^2 u}{\partial x^2} + \frac{\Delta x^2}{12} \frac{\partial^4 u}{\partial x^4} + O(\Delta x^4)$$

$$= \frac{\partial^2 u}{\partial x^2} + O(\Delta x^2)$$

ie. consistent with $\frac{\partial^2 u}{\partial x^2}$ and second-order accurate in space increment Δx .

$$Q4 c) i) \quad \frac{\partial u}{\partial x} + \frac{\partial u}{\partial t} = 0$$

$$\therefore \quad \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial x \partial t} = 0 \quad \text{and} \quad \frac{\partial^2 u}{\partial t \partial x} + \frac{\partial^2 u}{\partial t^2} = 0$$

$$\text{Since} \quad \frac{\partial^2 u}{\partial x \partial t} = \frac{\partial^2 u}{\partial t \partial x}, \quad \underline{\underline{\frac{\partial^2 u}{\partial x^2} = \frac{\partial^2 u}{\partial t^2} = -\frac{\partial^2 u}{\partial x \partial t}}}$$

ii). The Lax-Wendroff equation becomes:

$$\frac{\partial u}{\partial t} + \frac{\Delta t}{2} \left(\frac{\partial^2 u}{\partial t^2} \right) + O(\Delta t^2) + \frac{\partial u}{\partial x} + O(\Delta x^2) = \frac{\Delta t}{2} \left[\frac{\partial^2 u}{\partial x^2} + O(\Delta x^2) \right]$$

Since $\frac{\Delta t}{2} \frac{\partial^2 u}{\partial t^2} = \frac{\Delta t}{2} \frac{\partial^2 u}{\partial x^2}$ we can cancel the terms which are first-order accurate in time interval Δt to get an equation which is second-order accurate in both space and time.

$$\underline{\underline{\frac{\partial u}{\partial t} + O(\Delta t^2) + \frac{\partial u}{\partial x} + O(\Delta x^2) = 0}}$$

This has been achieved without using centred differences in time.

Q5

Model of data: $\hat{y}_i = a + bx_i$ a) if Assume all measurement error occurs in measurements of \hat{y}_i , y_i

$$\therefore y_i = a + bx_i + \varepsilon_i$$

The least squares estimate minimizes the sum of the squares of the distances of data points to the straight line; E where:

$$E = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum_{i=1}^n \varepsilon_i^2 = \sum_{i=1}^n (y_i - (a + bx_i))^2$$

The minimum E occurs for values of a and b such that:

$$\frac{\partial E}{\partial a} = 0 \quad \text{and} \quad \frac{\partial E}{\partial b} = 0$$

$$\frac{\partial E}{\partial a} = 0 \quad \Longrightarrow \quad -2 \sum_{i=1}^n (y_i - (a + bx_i)) = 0$$

$$\frac{\partial E}{\partial b} = 0 \quad \Longrightarrow \quad -2 \sum_{i=1}^n x_i (y_i - (a + bx_i)) = 0$$

Minimum least squares error solution for a and b :

$$na + b \sum_{i=1}^n x_i = \sum_{i=1}^n y_i$$

$$a \sum_{i=1}^n x_i + b \sum_{i=1}^n x_i^2 = \sum_{i=1}^n x_i y_i$$

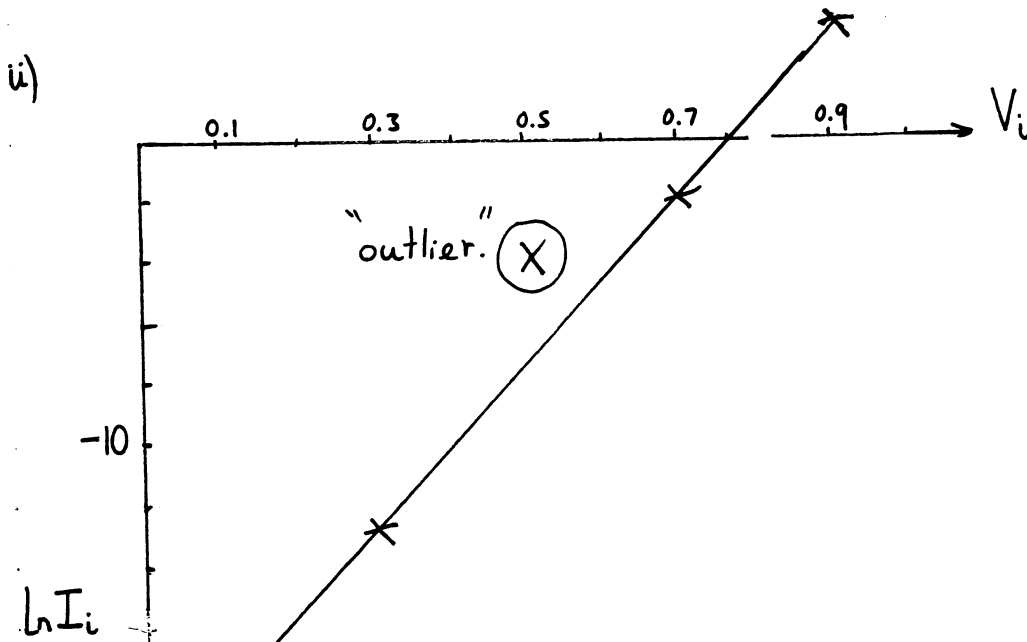
ii) If the error occurs in the measurement of x_i only then minimise the distance measured in the x -direction instead.

Q5b.

$$i) I_i = I_0 e^{\frac{V_i}{V_s}}$$

$$\therefore \ln I_i = \ln I_0 + \left(\frac{1}{V_s}\right) V_i$$

$$\text{cf } y_i = a + b x_i \quad \text{where } a = \ln I_0 \text{ and } b = 1/V_s$$



For correct 4 measurements (i.e. exclude $V=0.5$, $\ln I = -4$ measurement)

$$\begin{aligned} n &= 4 \\ \sum x_i &= 2.0 \\ \sum x_i^2 &= 1.4 \\ \sum x_i y_i &= -3.5 \\ \sum y_i &= -29 \end{aligned}$$

Least squares estimates for a and b satisfy

$$\begin{aligned} 4a + 2b &= -29 \\ 2a + 1.4b &= -3.5 \end{aligned}$$

$$\Rightarrow a = -21, \quad I_0 = 7.58 \times 10^{-10} \\ b = 27.5, \quad \underline{V_s = 0.036V}$$

iii). $V=0.9$ measurement is twice as accurate and the distance to line should be weighted by $\sqrt{2}$. Add this measurement twice so that $n=5$ and $V=0.9$ appears twice.

Q6 a). For a signal $x(t)$ with Fourier Transform $X(\omega)$

$$X(\omega) = \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt$$

let $y(t) = x(t) e^{j\omega_0 t}$ have Fourier Transform $Y(\omega)$.

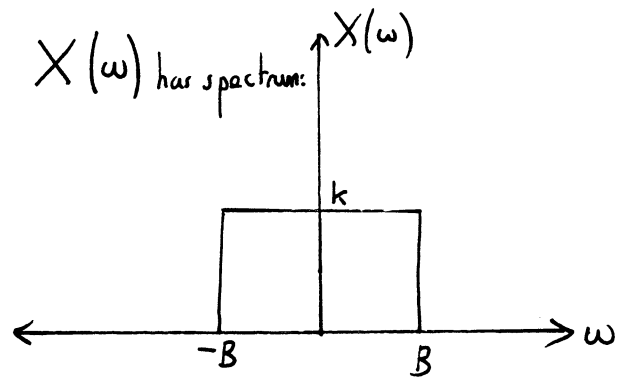
$$Y(\omega) = \int_{-\infty}^{\infty} (x(t) e^{j\omega_0 t}) e^{-j\omega t} dt$$

$$= \int_{-\infty}^{\infty} x(t) e^{-j(\omega - \omega_0)t} dt$$

$$= X(\omega') \quad \text{where } \omega' = \omega - \omega_0$$

$$\underline{Y(\omega) = X(\omega - \omega_0)} \quad [\text{Frequency shift}]$$

b) $y(t) = x(t) \cdot s(t)$, and $X(\omega)$ has spectrum:



$$i) s(t) = \cos \omega_0 t = \frac{1}{2} [e^{j\omega_0 t} + e^{-j\omega_0 t}]$$

$$\therefore y(t) = \frac{x(t)}{2} [e^{j\omega_0 t} + e^{-j\omega_0 t}]$$

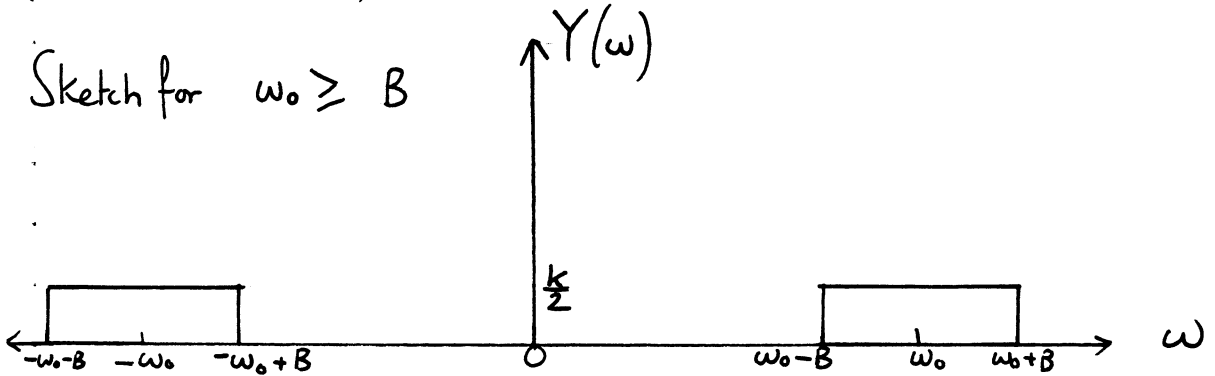
Q6b(cont)

Using result of part(a).

$$\therefore Y(\omega) = \frac{X(\omega - \omega_0)}{2} + \frac{X(\omega + \omega_0)}{2}$$

(i.e. modulation theorem)

Sketch for $\omega_0 \geq B$



i.e. frequency shift in modulation.

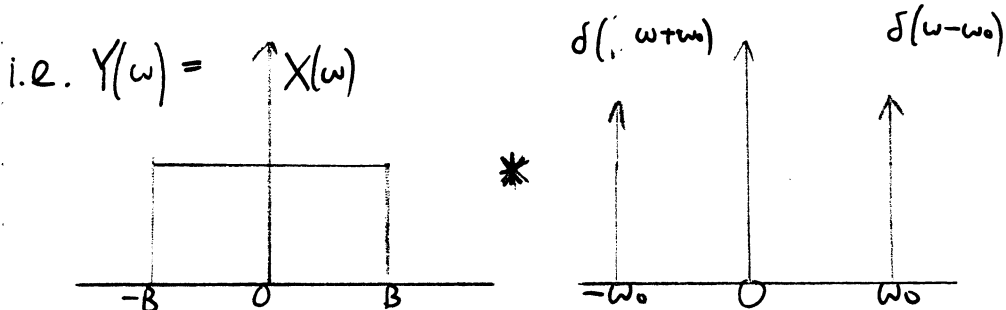
Note alternative method

From convolution theorem, multiplication in time domain leads to convolution in the frequency domain.

If $y(t) = x(t) \cdot g(t)$

then $Y(\omega) = \frac{1}{2\pi} X(\omega) * S(\omega)$

where $S(\omega) = \pi [\delta(\omega - \omega_0) + \delta(\omega + \omega_0)]$



$$\therefore Y(\omega) = \frac{1}{2} \int_{-\infty}^{\infty} X(\Omega) \delta(\omega - \omega_0 - \Omega) d\Omega + \frac{1}{2} \int_{-\infty}^{\infty} X(\Omega) \delta(\omega + \omega_0 - \Omega) d\Omega$$

$$Y(\omega) = \frac{X(\omega - \omega_0)}{2} + \frac{X(\omega + \omega_0)}{2}$$

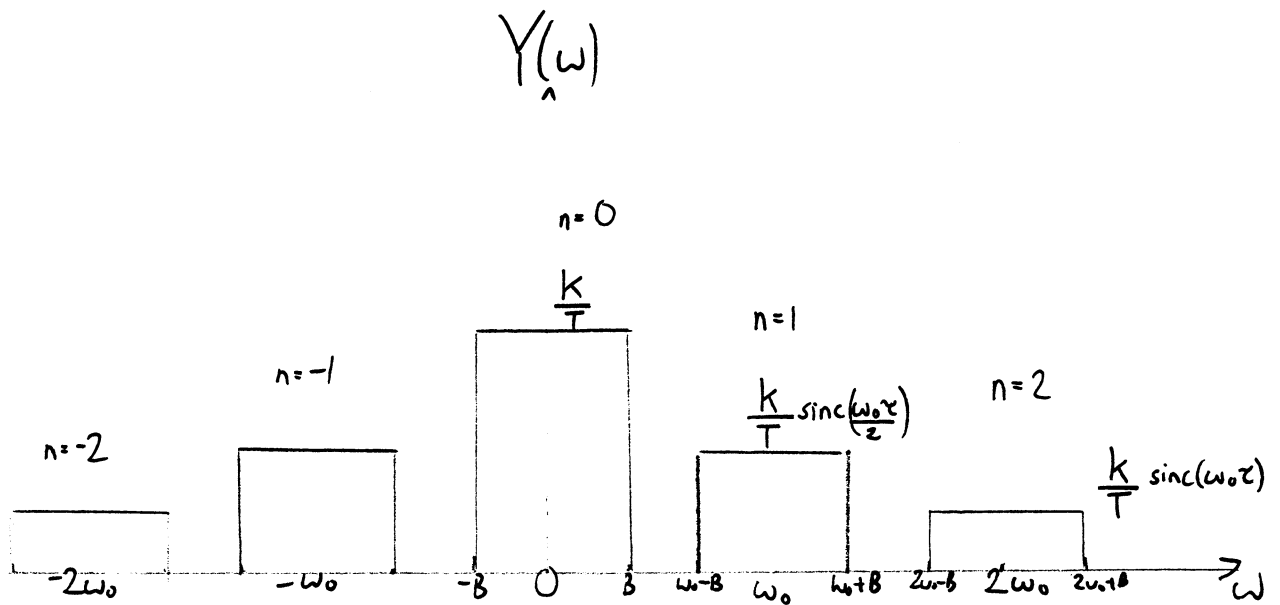
Q.6 ii). $y(t) = \frac{x(t)}{T} \sum_{n=-\infty}^{\infty} \text{sinc}\left(\frac{n\omega_0\tau}{2}\right) e^{jn\omega_0 t}$

$$y(t) = \frac{1}{T} \sum_{n=-\infty}^{\infty} \text{sinc}\left(\frac{n\omega_0\tau}{2}\right) x(t) e^{jn\omega_0 t}$$

Using frequency shift result of (a):

$$\therefore Y(\omega) = \frac{1}{T} \sum_{n=-\infty}^{\infty} \text{sinc}\left(\frac{n\omega_0\tau}{2}\right) X(\omega - n\omega_0)$$

Note: $s(t)$ is a pulse-train.



iii). $\tau \rightarrow 0 \quad s(t) \rightarrow \delta_p(t)$ i.e. impulse train

$s(t) \rightarrow \frac{1}{T} \sum_{n=-\infty}^{\infty} 1 \cdot e^{jn\omega_0 t}$ (i.e. Impulse train Fourier series)

since $\text{sinc}\left(\frac{\omega\tau}{2}\right) \rightarrow 1$ as $\tau \rightarrow 0$

$$\therefore \text{spectrum } Y(\omega) \rightarrow \frac{1}{T} \sum_{n=-\infty}^{\infty} X(\omega - n\omega_0)$$

as in ideal sampling by impulse train.

$$\begin{aligned}
 \text{b.iii. As } z \rightarrow T \quad \sin \frac{n\omega_0 z}{2} &\rightarrow \text{sinc} \frac{n\omega_0 T}{2} = \text{sinc}(n\pi) \\
 &= 0 \quad n \neq 0 \\
 &= 1 \quad n = 0
 \end{aligned}$$

$$\therefore \underline{Y(\omega) \rightarrow \frac{1}{T} X(\omega)}$$

i. e. no sampling but scaling by $1/T$. Obvious since $s(t) \rightarrow \frac{1}{T}$ and $y(t) = \frac{1}{T} x(t)$.

Q7)

a) Sampling frequency = $f_s = 20 \text{ kHz}$ Sample period $T = 50 \mu\text{s}$
 no. of samples, $N = 1024$

i). For band limited signal $f_s \geq 2 f_b$
 \therefore maximum frequency after anti-aliasing filter, $f_b = \underline{10 \text{ kHz}}$

ii) frequency spacing $\Delta f = \frac{f_s}{N} = \frac{20000}{1024} = \underline{19.5 \text{ Hz}}$

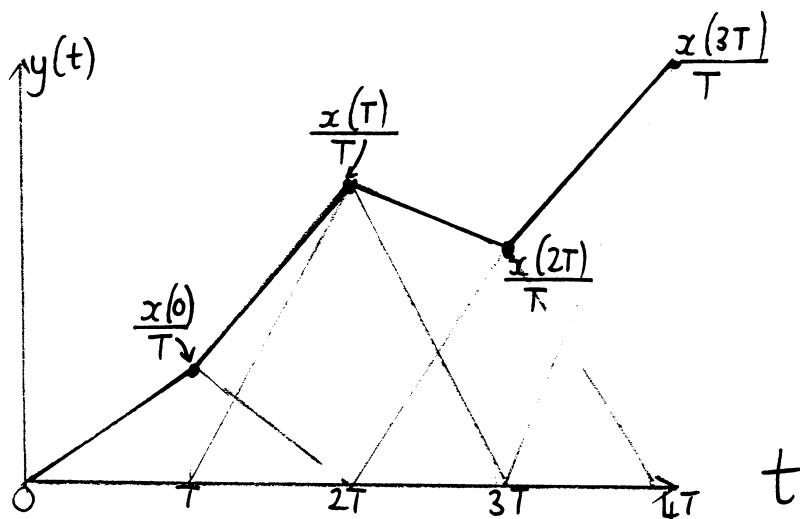
or $\Delta f = \frac{1}{T_L} = \frac{1}{NT} = \frac{1}{1024 \times 50 \times 10^{-6}} = 19.5 \text{ Hz}$

b). $x_s(t) = \sum_{-\infty}^{\infty} x(nT) \delta(t - nT)$

$$y(t) = h(t) * x_s(t)$$

$$= h(t) * \sum_{-\infty}^{\infty} x(nT) \delta(t - nT)$$

$$y(t) = \sum_{-\infty}^{\infty} x(nT) h(t - nT)$$



i.e. linear interpolation of samples, delayed by T , scaled by $\frac{1}{T}$. Used in recovery of

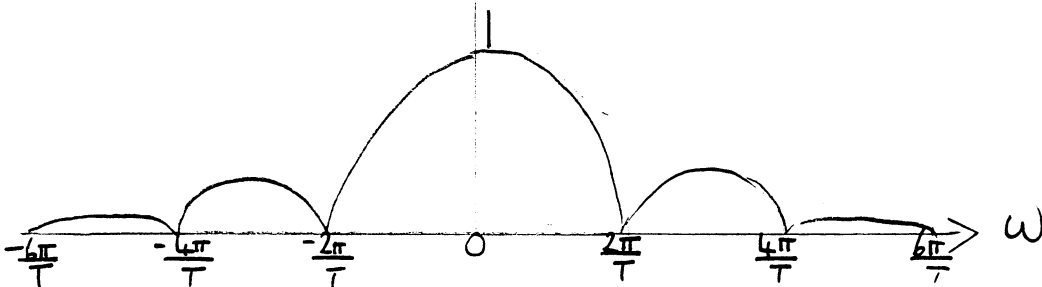
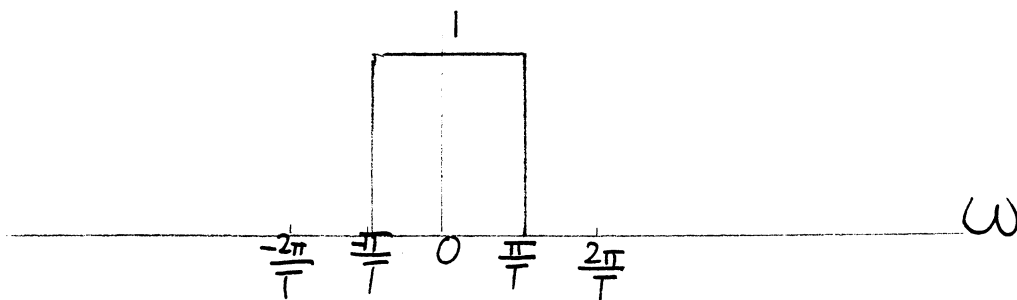
Q7b.

From databook for triangle pulse shifted (delayed) by T .

$$H(\omega) = e^{-j\omega T} \cdot \text{sinc}^2\left(\frac{\omega T}{2}\right)$$

$$= \left[\frac{4}{\omega^2 T^2} \sin^2 \frac{\omega T}{2} \right] e^{-j\omega T}$$

$$\therefore |H(\omega)| = \text{sinc}^2\left(\frac{\omega T}{2}\right)$$

Filter performing linear interpolation $|H(\omega)|$ Ideal filter to recover $x(t)$ from $x_s(t)$:
 $H_{\text{ideal}}(\omega)$ 

Note linear interpolator introduces high-frequency distortion. Ideal filter is impractical.

Q8 a). For a probability density function $f(x)$ of a random variable X the moment-generating function is defined by:

$$M_X(s) = \int_{-\infty}^{\infty} f(x) e^{-sx} dx = E(e^{-sX})$$

(Note alternative definitions exist: $M_X(t) = E(e^{tX})$).

i) Moments of the distribution can be computed from $M_X(s)$ by differentiation (if possible):

$$\frac{d^n M_X(s)}{ds^n} \Big|_{s=0} = (-1)^n E(X^n)$$

eg. $E(X) = \int_{-\infty}^{\infty} x f(x) dx = - \frac{d M_X(s)}{ds} \Big|_{s=0}$

$$E(X^2) = \int_{-\infty}^{\infty} x^2 f(x) dx = \frac{d^2 M_X(s)}{ds^2} \Big|_{s=0}$$

ii) Moment-generating functions can be used to derive the probability density functions of sums of independent random variables (see (b)). (reproductive properties).

eg. If $Z = X + Y$

$$M_Z(s) = M_X(s) M_Y(s)$$

If X and Y are normally distributed random variables, Z will also have a normal distribution.

$$8b). \quad X \sim N(\mu_1, \sigma_1)$$

$$Y \sim N(\mu_2, \sigma_2)$$

$$(-Y) \sim N(-\mu_2, \sigma_2)$$

If $Z = X - Y$ and X and Y are independent

$$f_Z(z) = \int_{-\infty}^{\infty} f_X(x) f_Y(x-z) dx = \int_{-\infty}^{\infty} f_X(x) f_{-Y}(z-x) dx$$

i.e. convolution of pdf of X and $-Y$.

By using moment-generating functions (similar to Laplace transforms) the moment generating function can be obtained by multiplication.

$$\begin{aligned} \therefore M_Z(s) &= M_X(s) M_{-Y}(s) \\ &= e^{(-s\mu_1 - \frac{\sigma_1^2 s^2}{2})} \cdot e^{s\mu_2 - \frac{\sigma_2^2 s^2}{2}} \\ &= e^{-s(\mu_1 - \mu_2) - \frac{s^2}{2}(\sigma_1^2 + \sigma_2^2)} \end{aligned}$$

This is the moment-generating function of a gaussian distribution:

$$\therefore f_Z(z) = \frac{1}{\sigma' \sqrt{2\pi}} e^{-\frac{(z-\mu')}{2\sigma'^2}} \quad \text{where } \begin{aligned} \mu' &= \mu_1 - \mu_2 \\ \sigma'^2 &= \sigma_1^2 + \sigma_2^2 \end{aligned}$$

$$\therefore \underline{Z \sim N(\mu_1 - \mu_2, \sqrt{\sigma_1^2 + \sigma_2^2})}$$

$$8c). X = \text{total weight} \sim N(W, 12)$$

$$Y = \text{can weight} \sim N(200, 9)$$

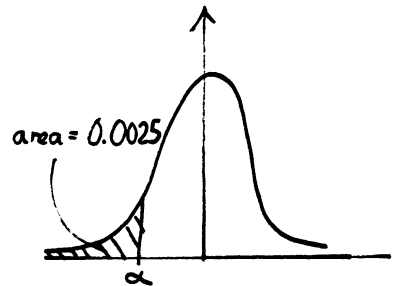
$$Z = \text{contents} = X - Y \sim N(W - 200, \sqrt{9^2 + 12^2})$$

$$\underline{Z \sim N(W - 200, 15)}$$

$$\therefore \frac{Z - (W - 200)}{15} \sim N(0, 1)$$

We must ensure that $\frac{1000 - (W - 200)}{15} = \alpha$

where $\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\alpha} e^{-\frac{u^2}{2}} du = 0.0025$



From datasheet $\underline{\alpha = -2.81}$

$$\therefore \frac{1000 - (W - 200)}{15} \leq -2.81$$

$$\therefore W \geq 1200 + 2.81 \times 15$$

$$\underline{W \geq 1242g.}$$

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