

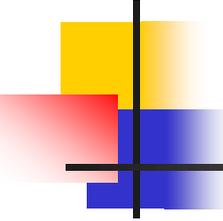
Fractals

Part 5 : Fractal compression

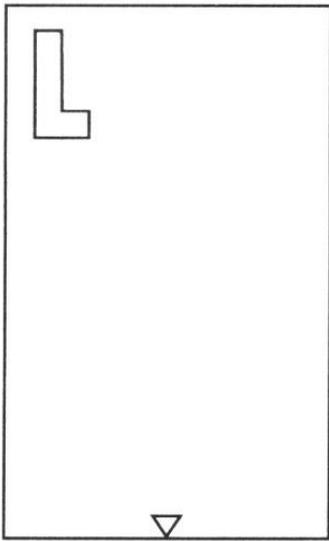


Martin Samuelčík

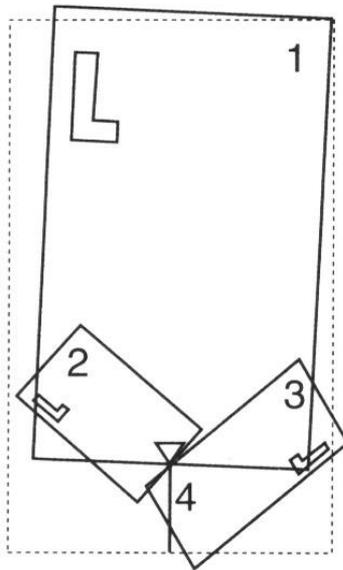
Department of Applied Informatics



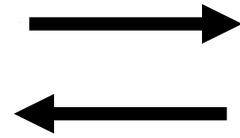
IFS



Initial Image



Stage 1





Using IFS

- Model natural objects
- Simulate natural cases
- Inverse problem
- Reconstructing objects
- Fractal interpolation
- Image compression and coding



Coding of IFS

- Let's have fractal as attractor of IFS
- We can describe this image very easily
- Perfect coding
- Independent of scale
- Perfect compression
- Complex shape \leftrightarrow low count of bits



Generalization

- Using previous approach for any image
- Good compression
- Finding similarities in image
- We want image as attractor
- Or his good approximation
- Progressive showing of image



Image

- Image of pixels – in discrete space
- Finite resolution
- Generalized image for IFS
- $I(x,y)$ in $\langle 0,1 \rangle$ for x,y in $\langle 0,1 \rangle$
- Infinite resolution
- Then it is member of $H(X)$



Metric on Images

- Comparing 2 images
- Defining contractive transformation
- Basic metric

- $\sup_{x,y \text{ in } <0,1>} |f(x,y) - g(x,y)|$

- Least square metric

- A_i, b_i are intensities of 2 images

- Minimization of

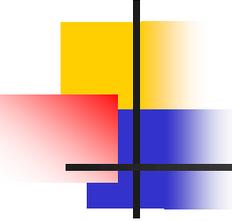
- R is then distance

$$R = \sum_{i=1}^n (s \cdot a_i + o - b_i)^2$$



Compression of images

- In pixel space
- Storing pixels and using data compression
- Storing coefficients of DCT transformations
- All in discrete space
- Jpeg, Gif, Png, Bmp ...



Collage theorem

- (X, d) complete metric space
- L in $H(X)$, $\varepsilon > 0$
- IFS $\{X, f_1, \dots, f_N\}$ with contr. factor s

$$h(L, \bigcup_{i=1}^N f_i(L)) < \varepsilon$$

- Then
$$h(L, x_W) < \frac{\varepsilon}{(1-s)}$$
- Where x_W is attractor of IFS $\{X, f_1, \dots, f_N\}$



Collage theorem 2

- If we cover precisely L with its affine copies, then attractor IFS approximate L with good precision
- For smaller ε we need more f_i
- Effective representation assume that transformations cover L and two transformation have no intersection

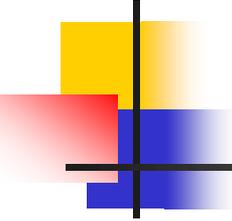


Improving IFS

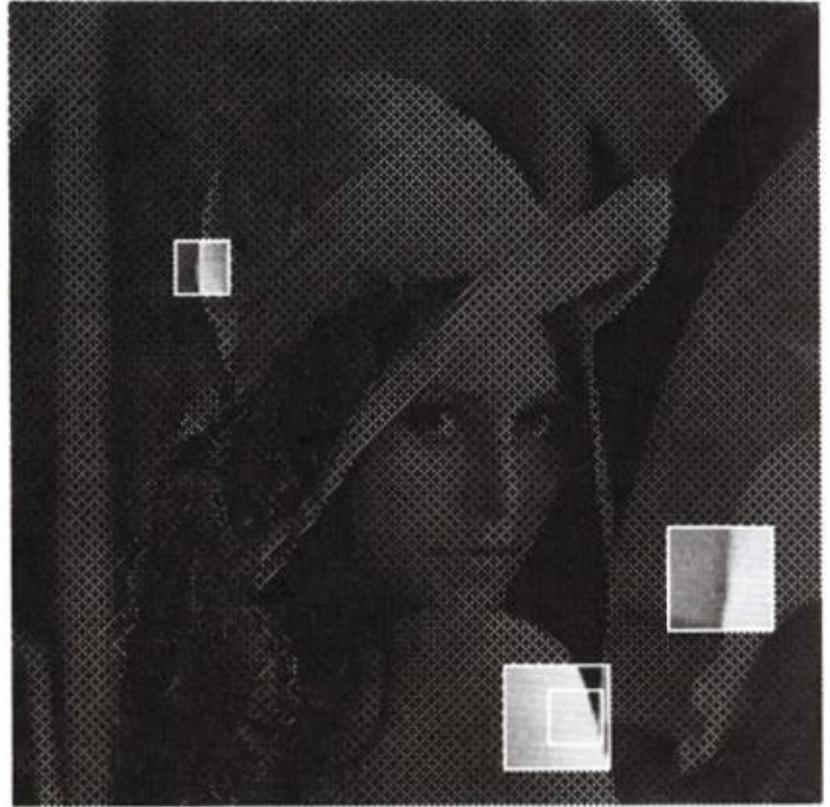
- $f_i: D_i \rightarrow R_i, i=1, \dots, N$

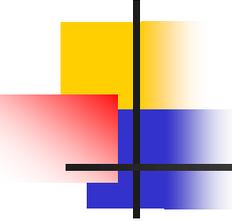
$$f_i: \begin{pmatrix} x \\ y \\ z \end{pmatrix} : \begin{pmatrix} a_i & b_i & 0 \\ c_i & d_i & 0 \\ 0 & 0 & s_i \end{pmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix} + \begin{pmatrix} e_i \\ f_i \\ o_i \end{pmatrix} \quad \bigcup_{i=1}^N R_i = I; R_i \cap R_j = \emptyset, i \neq j$$

- $f_i(I) = f_i(x, y, I(x, y))$
- s_i, o_i – contrast, brightness
- f_i is restricted to D_i
- Partitioned IFS (PIFS)



Transformations





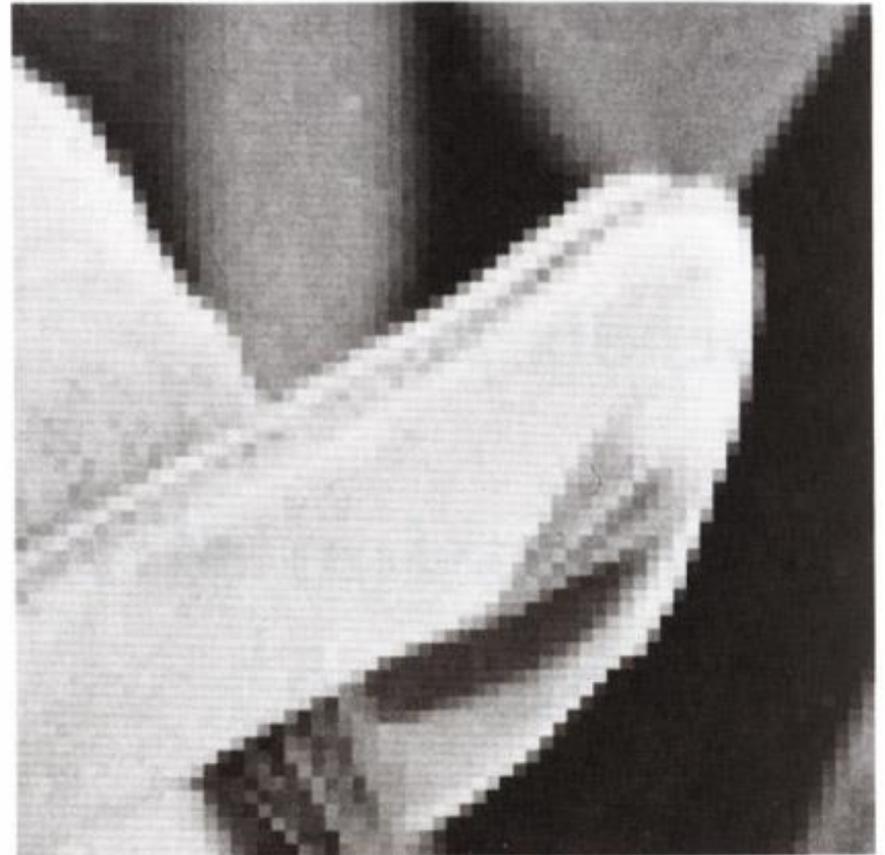
Fractal compression

- Barnsley
- Covered with copyright
- Perfect \leftrightarrow useless
- Need to be optimized
- Rapidly improved
- Now? Not used





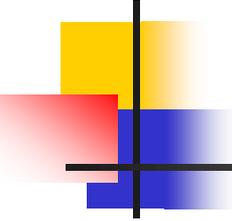
Fractals vs Pixels





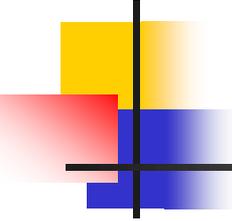
Encoding

- Now for given image I we want to find improved IFS $\{X, f_1, \dots, f_N\}$
- $W(I)$ should be very close to our image
$$I \approx I' = W(I') \approx W(I)$$
- Minimal value of $h(I \cap R_i, f_i(I))$
- Have to find D_i, R_i, s_i, o_i
- Store only these values

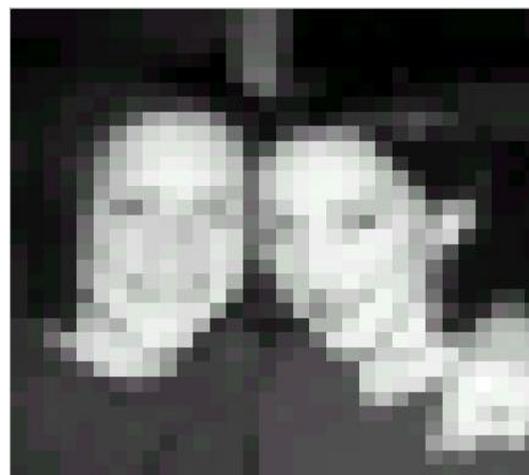


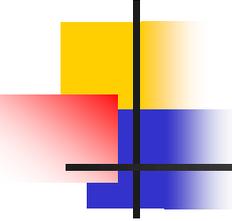
Decoding

- We have IFS
- We can start with any image
- Should have lot of steps
- Using deterministic or stochastic algorithm
- No pixelization = scale detail
- Need to decode whole



Decoding 2

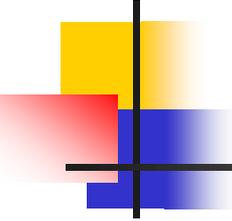




Simple example

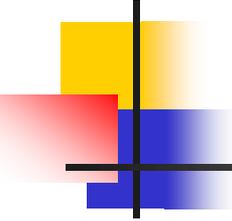
- 256 x 256 image
- R_1, \dots, R_{1024} – all non-overlapping 8x8 subimages
- D_1, \dots, D_{58081} – all 16x16 subimages
- For each R_i find D_i so that minimizes

$$h(I \cap R_i, f_i(D_i))$$

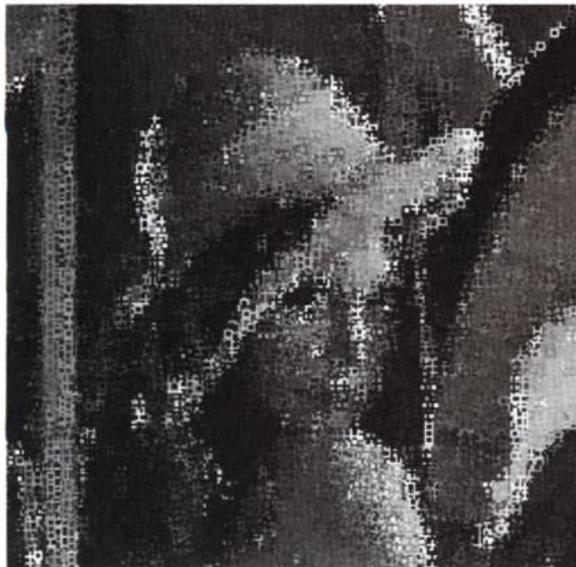
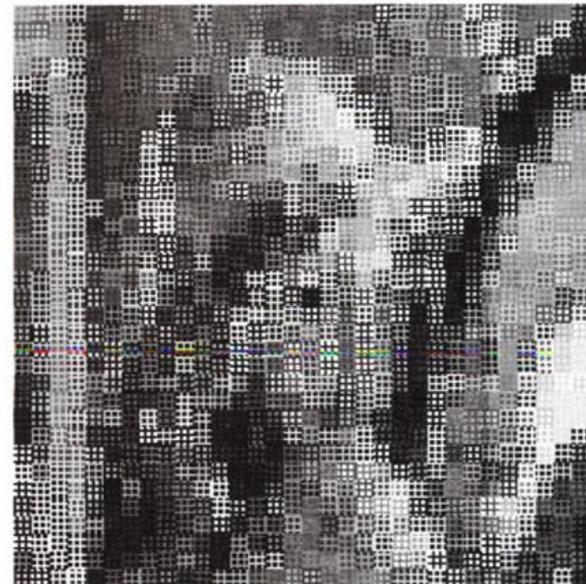
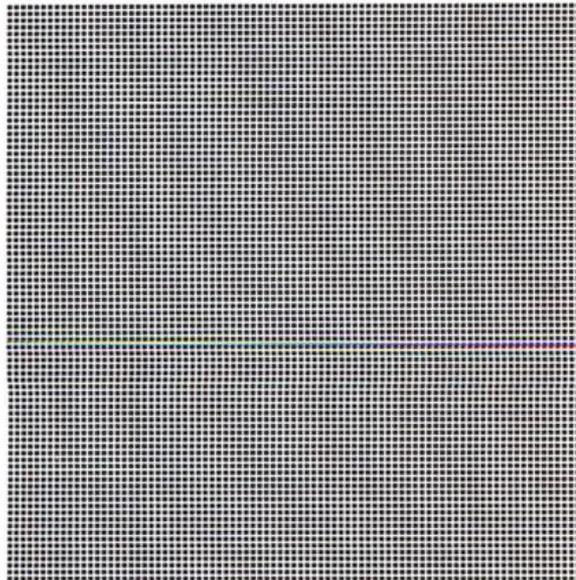


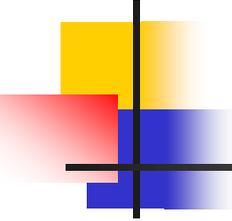
Simple example 2

- Minimalization using least square metric
- This metric gives us also s_i, o_i
- We get f_1, \dots, f_{1024}
- We store this system
- 65536 -> 3968
- With decoding improving detail 8x8, 4x4



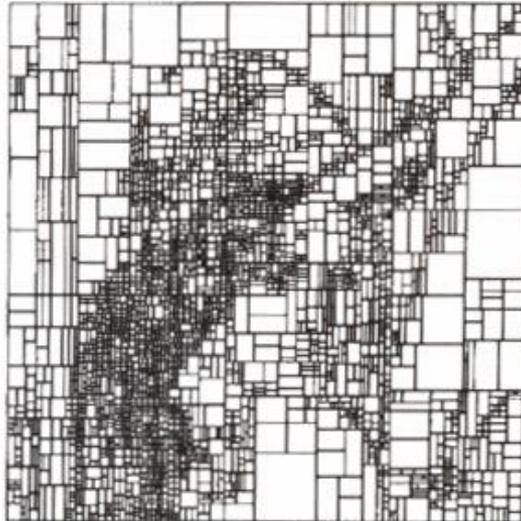
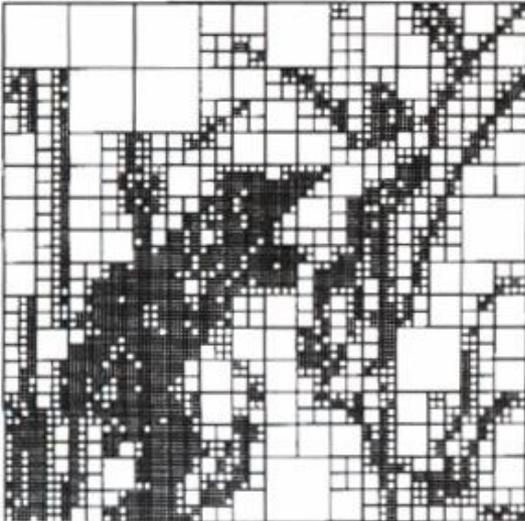
Result





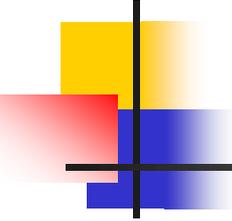
Partitioning image

- Uniform
- Quadtree, HV
- Triangular, Custom



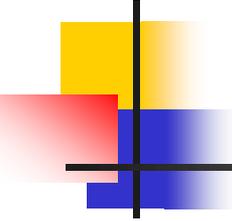
Other results





Optimizing

- Compression ratio \leftrightarrow fidelity
- Encoding time
- Choosing ranges
- Choosing domains

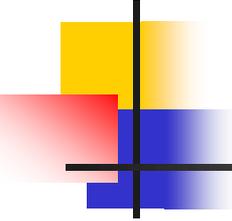


Fractal interpolation

- Image encoded using fractal compression is “pixelation free”
- Good for expanding images – bilinear, cubic spline, statistical interpolation
- PIFS is created, used for expansion (contaction) of image and then discarded

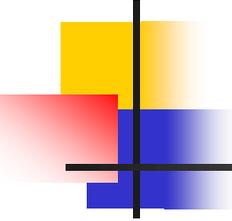
Fractal interpolation





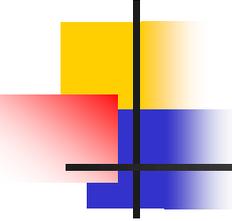
Search strategies

- Heavy brute force
- Light brute force
- Restricted area search
- Local spiral search
- Look same place
- Categorized search



Fractal compression

- Promising technology in the late 1980s
- Main competitor - JPEG
- Large advantage over JPEG at low image quality levels
- "Graduate Student Algorithm": lock a graduate student in a room with a computer until they solve your problem.



Fractal interpolation

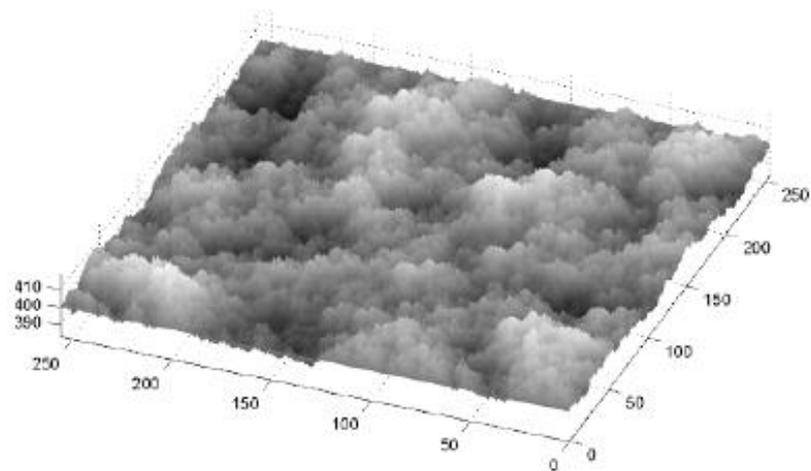
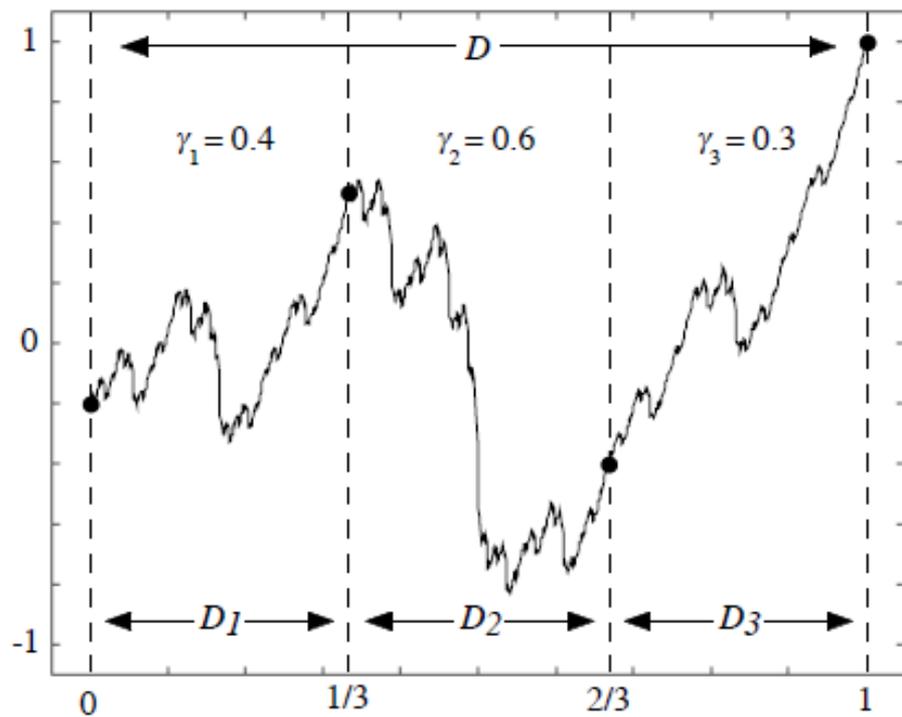
- Points $A_i = (x_i, y_i), i = 0, \dots, M$
- Define function w such that $f(x_i) = y_i$
- f -attractor of IFS (w_1, \dots, w_M)
- d_i is free parameter, $|d_i| < 1$

$$w_i \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} a_i & 0 \\ c_i & d_i \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} + \begin{pmatrix} e_i \\ f_i \end{pmatrix}; \quad i = 1, 2, \dots, M.$$

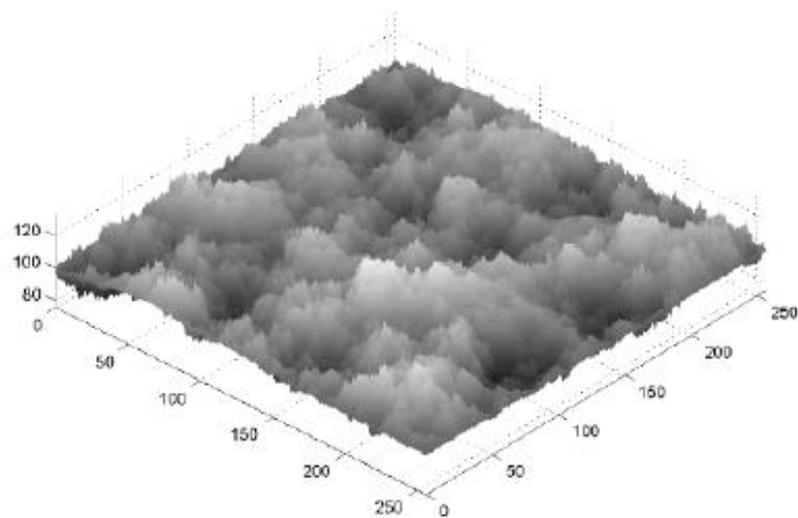
$$w_i \begin{pmatrix} x_0 \\ y_0 \end{pmatrix} = \begin{pmatrix} x_{i-1} \\ y_{i-1} \end{pmatrix} \quad \text{and} \quad w_i \begin{pmatrix} x_M \\ y_M \end{pmatrix} = \begin{pmatrix} x_i \\ y_i \end{pmatrix}; \quad i = 1, 2, \dots, M$$

$$\begin{aligned} a_i &= \frac{(x_i - x_{i-1})}{(x_M - x_0)} \\ c_i &= \frac{(y_i - y_{i-1})}{(x_M - x_0)} - d_i \frac{(y_M - y_0)}{(x_M - x_0)} \\ e_i &= \frac{(x_M x_{i-1} - x_0 x_i)}{(x_M - x_0)} \\ f_i &= \frac{(x_M y_{i-1} - x_0 y_i)}{(x_M - x_0)} - d_i \frac{(x_M y_0 - x_0 y_M)}{(x_M - x_0)} \end{aligned}$$

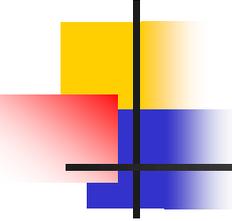
Interpolation



(a)



(b)



End

End of Part 5