la trasformata Mojette : venti anni di Tomografia (molto) Discreta

Jeanpierre GUEDON et al

Lab IRCCyN – Polytech Univ Nantes FRANCE

Tomo & Applications – Politectenico di Milano ITALIA The Mojette transform : 20 years of (very) Discrete Tomography

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la trasformata Mojette : 20 anni

Grazie

Nicolas Normand **Olivier Philippé** Florent Autrusseau **Benoit Parrein Pierre Evenou Pierre Verbert** Myriam Servières **Andrew Kingston Imants Svalbe** Chuanlin Liu **Aurore Arlicot** Henri Der Sarkissian



Yves Bizais Dominique Barba Nicole Burger Mark Barratt **Dietmar Eggeman** Sandrine Lecoq **Eloise Denis Peggy Subirats Tarraf Torfeh** Hadi Fayad **Jiazy Li Shakes Chandra** Zeeshan Ahmed 3

introduction

Mojette - bean

Mojette = fagiolo = bean		
augenbohne	pois chique black-eyed-pea	
costeño, frijol de costa		
	voamba (Mac	dagascar)
cowpea		dolique from China
cornille	mongette	dolique à œil noir
dolique mongette		niébé (Sénégal)
bannette (Provence)	cow bean	coco œil noir
		pois à vaches



introduction

$$Mf(k, l) = proj_f(b, p, q)$$

$$proj_{f}(b, p, q) = \sum_{k} \sum_{l} (f(k, l) \Delta(b + qk - pl))$$

With k,l,b,p,q integers

Initial work : Myron Katz 1978

outline

- 1. The Mojette transform with exact data
- 2. Tomographic reconstruction
- 3. Links with Fourier and FRT

- 1.1 The Mojette transform definition
- 1.2 Reconstruction theorem
- 1.3 Null space and fantoms
- **1.4 Applications**

1.1 The Mojette transform definition

Acts onto a regular pixel grid (k,l) e.g. rectangular hexagonal etc. $proj_f(b, p, q) = \sum_k \sum_l f(k, l) \Delta(b+qk-pl)$



$$proj_{f}(b, p=1, q=0) = \sum_{k} \sum_{l} f(k, l) \Delta(b-l)$$

1.1 The Mojette transform definition

Projection direction (p,q) $(p \in Z, q \in N)$ q>0 except for (p=1,q=0)



1.1 The Mojette transform definition

Projection direction (p,q)



 $proj_{f}(b,1,1) = \sum_{k} \sum_{l} (f(k,l) \Delta (b+k-l))$ $proj_{f}(b,-1,1) = \sum_{k} \sum_{l} (f(k,l) \Delta (b-k-l))$

1.1 The Mojette transform definition

The shape can be rectangular, convex, or not



2 figures with 12 pixels and a same set of projections



 $S = \{(10), (01), (11), (-11)\}$

1.1 The Mojette transform definition

$$proj_{f}(b, p, q) = \sum_{k} \sum_{l} f(k, l) \Delta(b + qk - pl)$$



Computing the projections of set

 $S = \{(10), (01), (11), (-11)\}$

1.1 The Mojette transform definition

$$proj_{f}(b, p, q) = \sum_{k} \sum_{l} f(k, l) \Delta(b + qk - pl)$$



the projections

the image

1.1 The Mojette transform definition

$$proj_{f}(b, p, q) = \sum_{k} \sum_{l} f(k, l) \Delta(b + qk - pl)$$



the projections

Typical Questions :

Can I reconstruct this shape from such a set of projections ?

If yes, which is the shortest algorithm (if no error)?

If no, how many solutions match the projections set ?

1.1 The Mojette transform definition in 3D and nD

Same definition in 3D and nD



1.1 The Mojette transform definition in 3D and nD

$$proj_{f}(b, p, q) = \sum_{k} \sum_{l} f(k, l) \Delta(b + P_{21}(\frac{k}{l}))$$

$$\boldsymbol{P}_{21} = \left| 1 - \frac{q}{p} \right|$$

Same definition in 3D and nD

$$proj_{f}(b_{1}, b_{2}, p, q, r) = \sum_{k} \sum_{l} \sum_{m} f(k, l, m) \Delta(\boldsymbol{B} + \boldsymbol{P}_{32} \begin{vmatrix} p \\ q \\ r \end{vmatrix})$$
$$\boldsymbol{B} = \begin{vmatrix} b_{1} \\ b_{2} \end{vmatrix} \qquad \boldsymbol{P} = \begin{vmatrix} 10 - p/r \\ 01 - q/r \end{vmatrix}$$

1.2 Reconstruction theorem

$$proj_{f}(b, p, q) = \sum_{k} \sum_{l} f(k, l) \Delta(b + qk - pl)$$



the projections

Questions :

Can I reconstruct this shape from such a set of projections ?

If yes, which is the shortest algorithm ?

1.2 Reconstruction theorem

$$proj_{f}(b, p, q) = \sum_{k} \sum_{l} f(k, l) \Delta(b + qk - pl)$$

Ph.D. Nicolas Normand 1997

Some pixels can be « backprojected » from their bin value since 1-1 relationship

the reconstruction process

the characteristic shape function

1.2 Reconstruction theorem

Ph.D. Nicolas Normand 1997



the reconstruction process

When this is done, new pixels become in 1-1 relationships



1.2 Reconstruction theorem

Ph.D. Nicolas Normand 1997



the reconstruction process

new pixels become in 1-1 relationships



1.2 Reconstruction theorem

Ph.D. Nicolas Normand 1997



the reconstruction process

and again ...



1.2 Reconstruction theorem

Ph.D. Nicolas Normand 1997



the reconstruction process

and again ...



1.2 Reconstruction theorem

Ph.D. Nicolas Normand 1997



We complete the reconstruction

One projection was not used

12 bins were used (= number of pixels)

We could have used other bins

the reconstruction process has linear complexity in # pixels & # projections

1.2 Reconstruction theorem

For a rectangular shape, Myron KATZ (78) proved:

For a rectangular shape of size (PxQ) , and a set of projections $S\!=\!\{(p_i,q_i),i\!=\!1\ldots N\}$

Reconstruc-ability of shape PxQ from set S <=> <u>N</u> <u>N</u>

$$\left(\sum_{i=1}^{N} |p_i| \ge P\right) \operatorname{or}\left(\sum_{i=1}^{N} |q_i| \ge Q\right)$$

1.2 Reconstruction theorem

rectangular shape P=4 Q=3

Reconstruc-ability of shape PxQ from $S = \{(10), (01), (11), (-11)\}$

<=>
$$(3 = \sum_{i=1}^{N} |p_i| \ge P = 4) \text{ or } (3 = \sum_{i=1}^{N} |q_i| \ge Q = 3)$$

Explain why : $S_1 = \{(01), (11), (-11)\}$ is a sufficient set to reconstruct



1.2 Reconstruction theorem

For a convex shape ?





2 figures with 12 pixels and a same set of projections



 $S = \{(10), (01), (11), (-11)\}$

1.2 Reconstruction theorem

For a convex shape ? Non optimal solution : insert it into a rectangular shape with 0 values





$$S = \{(10), (01), (11), (-11)\}$$

Does not change the projection values (change the number of bins)

1.2 Reconstruction theorem

For a convex shape ? Ph.D. Nicolas Normand 1997

Mathematical morphology with 2 Pixels Structuring Element (2PSE)

A projection direction <=> A 2PSE : {(0 0) ,(p,q)}

2PSE : eigenvector of dilation



1.2 Reconstruction theorem



A set of projections <=> shape obtained by the series of 2PSE dilations

(Normand-Guédon 97)





1.2 Reconstruction theorem

A set of projections S corresponds to the shape obtained by the series of dilations of 2PSE



1.2 Reconstruction theorem

the series of dilations of 2PSE is commutative, associative has a neutral element (p=q=0)



1.2 Reconstruction theorem

For a convex shape Sh , and a set of projections S={(pi, qi), i=1...N}

Reconstruc-ability of shape Sh from set S <=> The shape S generated by projections set S Can not be inserted into Sh



In the example, S just identically fit Sh => the reconstruction is not possible



1.2 Reconstruction theorem

Corollary Ph.D. Nicolas Normand 1997 When building a shape S by 2PSE dilation series of S And suppressing ANY border pixel of S to define Sh Allows for Reconstruc-ability of shape Sh from set S

In the example, S can not fit Sh => the reconstruction is possible



Sh

1.2 Reconstruction theorem

Checking ...


1.2 Reconstruction theorem



1.2 Reconstruction theorem



1.2 Reconstruction theorem



1.2 Reconstruction theorem



1.2 Reconstruction theorem



1.2 Reconstruction theorem

Ph.D. Nicolas Normand 1997

For a convex shape Sh , and a set of projections S={(pi, qi), i=1...N}

Reconstruc-ability of shape Sh from set S with Normand's algorithm <=>

The shape S, generated by the series of dilations using the 2PSE corresponding to projections set S, can not be inserted into Sh

1.2 Reconstruction theorem in 3D and nD

Ph.D. Pierre Verbert 2004 (with Nicolas Normand)

For a 3D convex shape Sh, and a set of projections S={(pi, qi, ri), i=1...N}

Reconstruc-ability of shape Sh from set S with Normand's algorithm <=>

The shape S, generated by the series of dilations using the 2PSE corresponding to projections set S, can not be inserted into Sh

1.3 Null space and phantoms

What is a phantom (or ghost or switching component) ?

How to build a phantom ?

What is the use of a phantom ?

1.3 Null space and phantoms



1.3 Null space and phantoms



1.3 Null space and phantoms



1.3 Null space and phantoms



1.3 Null space and phantoms



1.3 Null space and phantoms



1.3 Null space and phantoms



1.3 Null space and phantoms



1.3 Null space and phantoms



1.3 Null space and fantoms

building a phantom : by simple convolution



1.3 Null space and fantoms



1.3 Null space and fantoms



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1.3 Null space and fantoms

 $S6 = \{(1 \ 1)(-1 \ 1)(2 \ 1)(1 \ 2)(-1 \ 2)(1 \ 0)\}$



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Larger switching components



S8={ (1,0)(0,1) (1 1)(-1 1) (2 1)(1,2) (-1,2)(-2 1)}

la trasformata Mojette : 20 anni

Larger switching components



S9={ (1,0)(0,1) (1 1)(-1 1) (2 1)(1,2) (-1 2)(-2 1) (3 1)}

1.3 Null space and fantoms

Example

Take our convex shape Sh

 $S = \{(01), (11), (-11)\}$



1.3 Null space and fantoms

Perform dilation series





 $S = \{(01), (11), (-11)\}$ The resulting shape S Can be inserted into Sh

=> No reconstruct-ability (no unicity of the reconstruction)

1.3 Null space and fantoms



Equivalent process : making erosion series of Sh do not lead to empty set



1.3 Null space and fantoms



Erosion of Sh by 2PSE (0 1)



1.3 Null space and fantoms



Erosion of resulting shape by 2PSE (11)



1.3 Null space and fantoms



Erosion of resulting shape by 2PSE (-1 1)



1.3 Null space and fantoms

Incomplete reconstruction theorem (Philippé-Guédon 1997)





1.3 Null space and fantoms

Incomplete reconstruction theorem (Philippé-Guédon 1997)

Linear algebra – projector :

E = Im(f) + Ker(f)





1.3 Null space and fantoms

Incomplete reconstruction theorem (Philippé-Guédon 1997)

Linear algebra – projector :

E = Im(f) + Ker(f)





1.3 Null space and fantoms

Incomplete reconstruction theorem

The Mojette kernel is totally described by locations of non-eroded pixels onto which the phantom can be placed (= rank of Ker). Image is recovered by inverse Mojette algorithm after setting 0 onto non eroded pixels



1.3 Null space and fantoms

Incomplete reconstruction theorem

Notice that E is just a vectorial subspace composed of pixels



1.3 Null space and fantoms

Incomplete reconstruction theorem

when E has quantized pixels (ie binary / ternary) then the number of solutions is finite and all solutions are described here



- **1.4 Applications**
 - Error correcting code
 - **Distributed storage**
 - Network protocol
 - Watermarking
1.4 Applications

Error correcting code, optimal codes ?

Hamming H(7,4) H(15,11) H(31,26) ... : detect and correct 1 binary error

Other linear codes in between ?

1.4 Applications binary values

between Hamming H(7,4) and H(15,11) :



1.4 Applications

Moj(11,7)

7 initial bits oi 11 send bj



$$\begin{split} & \left(\Sigma_0 \!=\! \sum_{i=1}^7 o_i \right) \quad \begin{array}{l} \Sigma_1 \!=\! b_1 \!+\! b_2 \!+\! b_3 \\ & \left(\Sigma_2 \!=\! b_4 \!+\! b_5 \!+\! b_6 \!+\! b_7 \right) \\ & \Sigma_3 \!=\! b_8 \!+\! b_9 \!+\! b_{10} \!+\! b_{11} \end{split}$$

$$(\Sigma_0 \!=\! \Sigma_1 \!=\! \Sigma_2 \!=\! \Sigma_3)$$

1.4 Applications between Hamming H(7,4) and H(15,11) :

Moj(11,7)

At reception, computes

$$\Sigma_1 = b_1 + b_2 + b_3$$

($\Sigma_2 = b_4 + b_5 + b_6 + b_7$)
 $\Sigma_3 = b_8 + b_9 + b_{10} + b_{11}$



 $(CASE 0: (\Sigma_1 = \Sigma_2 = \Sigma_3): NO ERROR DETECTED)$

1.4 Applications

At reception, computes $\Sigma_1 = b_1 + b_2 + b_3$ $(\Sigma_2 = b_4 + b_5 + b_6 + b_7 + b_8)$ $\Sigma_3 = b_9 + b_{10} + b_{11} + b_{12}$

 $(CASE 1: (\Sigma_1 \neq (\Sigma_2 = \Sigma_3)))$



The error is located on projection (1 0) => first, only use the 2 other projections

1.4 Applications

 $(CASE 1: (\Sigma_1 \neq (\Sigma_2 = \Sigma_3)))$

The error is located on projection (10)

$$\begin{pmatrix} \Sigma_2 = b_4 + b_5 + b_6 + b_7 \\ \Sigma_3 = b_8 + b_9 + b_{10} + b_{11} \end{pmatrix}$$

After partial reconstruction, the phantom is left :

$$o_1 + o_3 = b_{11}$$

 $(o_1 + o_5 = b_5)$
 $o_5 + o_7 = b_9$
 $o_3 + o_7 = b_7$

Now, we also know that 2 of 3 binary value of (1 0) are good and one is not

1

1

-1



1.4 Applications

$$(CASE 1: (\Sigma_{1} \neq (\Sigma_{2} = \Sigma_{3})))$$

Always true : $o_{1} + o_{3} = b_{11}$
 $(o_{1} + o_{5} = b_{5})$
 $o_{5} + o_{7} = b_{9}$
 $o_{3} + o_{7} = b_{7}$

With only 1 system over 3 true:



And with respect to : $(\Sigma_1 \neq (\Sigma_2 = \Sigma_3)) =$ Locate the error

h0

1.4 Applications

$$(CASE: (\Sigma_1 = \Sigma_2) \neq \Sigma_3) \qquad \begin{vmatrix} o_2 + o_6 = b_4 \\ o_1 + o_5 = b_5 \\ o_1 + o_2 = b_1 \\ o_3 + o_4 + o_5 + o_6 = b_2 \end{vmatrix} \qquad \begin{array}{c} b_9 \\ b_1 \\ b_1$$

Only 1 system over 4 is correct Since only 1 location for the phantom

$$\begin{vmatrix} \bar{b}_8 = o_6 \\ b_9 = o_5 + o_7 \\ b_{10} = o_2 + o_4 \\ b_{11} = o_1 + o_3 \end{vmatrix}$$

$$\begin{vmatrix} b_8 = o_6 \\ \bar{b}_9 = o_5 + o_7 \\ b_{10} = o_2 + o_4 \\ b_{11} = o_1 + o_3 \end{vmatrix}$$

$$\begin{vmatrix} b_8 = o_6 \\ b_9 = o_5 + o_7 \\ \bar{b}_{10} = o_2 + o_4 \\ b_{11} = o_1 + o_3 \end{vmatrix}$$

$$\begin{vmatrix} b_8 = o_6 \\ b_9 = o_5 + o_7 \\ \bar{b}_{10} = o_2 + o_4 \\ \bar{b}_{10} = o_2 + o_4 \\ \bar{b}_{11} = o_1 + o_3 \end{vmatrix}$$

$$\begin{vmatrix} b_8 = o_6 \\ b_9 = o_5 + o_7 \\ \bar{b}_{10} = o_2 + o_4 \\ \bar{b}_{10} = o_2 + o_4 \\ \bar{b}_{11} = o_1 + o_3 \end{vmatrix}$$

And with respect to : $((\Sigma_1 = \Sigma_2) \neq \Sigma_3)$ => Locate the error

-1

b3

b2

b1

1.4 Applications

And with respect to : $((\Sigma_1 = \Sigma_3) \neq \Sigma_2) =>$ Locate the error

1.4 Applications Distributed storage

What exactly happens when you store A file of 1MB onto Google, Facebook or other ?

In order to recover your file with a sufficient probability (> 0.9999) the file has to be duplicated 3 times : 3MB stored

Instead, with the same probability (> 0.9999) store 1.5 MB !

Store redundant Mojette projections

1.4 Applications Distributed storage

Put the file into rectangular shape (Px3) Compute projections set : $S = \{(01), (11), (-11)(21)(-21)\}$

Any subset of 3 over 5 reconstruct the shape Store each projection onto a different disk



1.4 Applications Distributed storage







Linux / Windows / Mac OS





Content Storage Virtualisation Cloud Computing Big Data

RozoFS inc

Uses Mojette transform to store files 1 server = 1 projection

Interest 1: 1 server failed =>only 1 projection missing **Interest 2: read projections** in a parallel way

1.4 Applications Distributed storage





1.4 Applications wavelet image transmission

2001 Ph.D. Benoit Parrein

« geometric buffer »



1.4 Applications wavelet image transmission







1.4 Applications wavelet image transmission



1.4 Applications wavelet image transmission



1.4 Applications wavelet image transmission

2001 Ph.D. Benoit Parrein



1.4 Applications adhoc Network protocol



From OLSR

MultiPath – OLSR B. Parrein, J. Yi, S. David

1.4 Applications Watermarking



1.4 Applications Watermarking

Ph.D. Florent Autrusseau 2002



1.4 Applications Watermarking

original



watermark



Ph.D. Florent Autrusseau 2002

Watermarked image



outline

- 1. The Mojette transform with exact data
- 2. Tomographic reconstruction
- 3. Links with Fourier and FRT

2. Tomographic Mojette reconstruction

- 2.1 Binary-Ternary Mojette
- 2.2 From Radon to Mojette space
- 2.3 Discrete rotations

2. Tomographic Mojette reconstruction

2.1 Binary-Ternary Mojette

2.2 From Radon to Mojette space

2.3 Discrete rotations

Katz criteria holds for real values

Idea : Negative redundancy & Use of phantoms

Works with Chuanlin LIU – Imants Svalbe

« The Mojette line algorithm» 2004 Ph. D. of Pierre Verbert

Binary image Integer addition



« The Mojette line algorithm»

2004 Ph. D. Pierre Verbert

A bin sums of n pixels

If bin = 0 the line is zero If bin=n the line is full of « 1 »



Bin sum of n pixels If bin = 0 the line is zero If bin=n the line is full of « 1 »



Bin sum of n pixels If bin = 0 the line is zero If bin=n the line is full of « 1 »



« The Mojette line algorithm»

- Bin sum of n pixels
- If bin = 0 the line is zero If bin=n the line is full of « 1 »



« The Mojette line algorithm»

12 bins reconstruct24 pixels ...



« The Mojette line algorithm»

conclusion

When the image is composed of compact objects the Mojette line can be of interest (for compression purposes)



2010 : The Mojette game

3 rules :

1-Each pixel is a number(0 to 9).

2-There are only 3 different numbers per grid.

3- A bin sums the pixels along the discrete line



2010 : The Mojette game

3 rules :

1-Each pixel is a number(0 to 9).

2-There are only 3 different numbers per grid.

3- A bin sums the pixels along the discrete line



- 2010 : The Mojette game
- Start with 1-1 relationship


- 2010 : The Mojette game
- Find third value
 - Third value = 0 or 1

If 1 : 5=3+1+1 And 6=3+1+1+1 But 8=?+?+? no



- 2010 : The Mojette game
- Find intersecting lines

6 = 3+3+0+0 13 = 5+5+3



- 2010 : The Mojette game
- Find intersecting lines

6 = 3+3+0+0 13 = 5+5+3















```
2010 : The Mojette game

Grid with possible ghost

Because a < b < c values

Such that

b - a = c - b

Here b - a = 2
```







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2013 : Ph.D. Chuanlin LIU

Suppose the image composed of 3 very different materials

(e.g. bone air water) Here 0 1 and 5



2013 : Ph.D. Chuanlin LIU

Summing 2 pixels

Build tables for all possible sums with 0 1 5

	0	1	2	5	6	10
0	2	1	0	1	0	0
1	0	1	2	0	1	0
5	0	0	0	1	1	2

Summing 4 pixels

SUMS		0	1	2	3	4	5	6	7	8	10	
	0	4	3	2	1	0	3	2	1	0	2	
Number of	1	0	1	2	3	4	0	1	2	3	0	
	5	0	0	0	0	0	1	1	1	1	2	

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This is a new « line backprojection »

2013 : Ph.D. Chuanlin LIU

When no more corespondence bins,

Find pixel from intersected lines (2 or several bins)



Here « 1 » is the pixel value from bins values 6=5+1 and 1=1+0+0

2013 : Ph.D. Chuanlin LIU

Here, we recover the entire image



2013 : Ph.D. Chuanlin LIU

Ternary 256x256 image
the set
$$(1,0), (0,1), (1,1), (-2,1), (2,1), (1,2), (-1,2),$$

 $(S = \{ (1,3), (-1,3), (3,1), (-3,1), (2,3), (-2,3), (3,2), (-3,2), \})$
 $(1,4), (-1,4), (3,4), (-3,4)$
 $(1,5), (-1,5), (5,1), (-5,1), (2,5), (-2,5)$



reconstructs the image with

$$(\sum_{i} |p_{i}| = 50, \sum_{i} |q_{i}| = 64)$$
 (Red = $\frac{\# bins}{\# pixels} - 1 = -0.56)$)

2013 : Ph.D. Chuanlin LIU

64x64 image with 3 projections

8 (red dots) pixels Not reconstructed

=> ghost Putting 1 pixel value solve for the ghost



PhD Myriam Servières dec 2005 (also PhD Andrew Kingston for FRT)

$$f_{i}(k,l) = M_{i}^{*}M_{i}f(k,l)$$

But considering only the possible I angles existing onto a NxN support (Farey-Haros N-1):

$$g(k,l) = (I-1)f(k,l) + \sum_{i=1}^{N} \sum_{j=1}^{N} f(i,j)$$

PhD Myriam Servières dec 2005



Mojette Tomographic scheme

4

6

4

PhD Myriam Servières 2005 **Taking Radon projections**

Approximating into (spline) Mojette space



PhD Myriam Servières dec 2005



Mojette Tomographic scheme

PhD Myriam Servières dec 2005



Mojette Tomographic scheme

PhD Myriam Servières dec 2005 Approximating into Mojette space



Farey-Haros 10



PhD Myriam Servières dec 2005

And the constant S relying projections and image

$$\sum_{i=1}^{N} \sum_{j=1}^{N} f(i, j) = \frac{1}{I} \sum_{n} \sum_{b} proj(b, p_{n}, q_{n}) = S$$

So simple :

$$f(k,l) = \frac{1}{(I-1)}(g(k,l) - S)$$

PhD Myriam Servières dec 2005

So simple :

$$f(k,l) = \frac{1}{(I-1)}(g(k,l) - S)$$

However ... for a 65x65 image The Farey-Haros series is 5040 angles !

Mojette Tomographic scheme



PhD Myriam Servières dec 2005



I=64I=128I=256IMSE=0.40MSE=0.31MSE=0.31MSE=0.31

I=512 MSE=0.30

MFBP with Poisson noise

PhD Myriam Servières dec 2005



I=64I=128I=256MSE=0.28MSE=0.18MSE=0.17

I=512 MSE=0.06

MCG with Poisson noise

PhD Henri der Sarkissian 2015 + Benoit Recur



FBPSARTReal acquisition 403 proj – 404 bins per proj

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PhD Henri der Sarkissian 2015 + Benoit Recur



Mojette FBP Mojette SART Real acquisition 403 proj – 404 bins per proj

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outline

- 1. The Mojette transform with exact data
- 2. Tomographic reconstruction
- 3. Links with Fourier and FRT

3. Links between Mojette and FRT

Finite Radon Transform Introduced by Matus & Flusser in 1993

Only for pYp grid with p prime generates (p+1) projections of p bins => NO Redundancy

Used and extended by Imants Svalbe & A. Kingston to any image size => torus Mojette

3. Links between Mojette and FRT

Finite Radon Transform FRT:

$$R(t,m) = \sum_{i=0}^{r} f(t+mi,i) \text{ for each } 0 \le t < p$$

Selection of the image pixels sampled for FRT projection R(t=3, m=2) for p = 7



3. Links between Mojette and FRT

Finite Radon Transform FRT: $R(t, m) = \sum_{i=0}^{p} f(t+mi, i) \text{ for each } 0 \le t < p$

image pxp Only (p+1) projections of p bins, each summing up p pixels

d	е	f	d	е	f	d	е	f
g	h	i	9	h	i	g	h	i
а	b -	c	a	β	С	—a	b	с
d	е	f	d	æ	_t _	d	е	f
g	h	i	g	h		g	,¥	i
а	b	с	а	b	С	а	b	с
Finite Radon Transform FRT:

image p=3
4 projections
of 3 bins, each
summing up 3 pixels



<u>b</u>

<u>e</u>

þ

<u>a</u>

Ø

Ø



С

b

а

a+b+c



Inverse Finite Radon Transform

backprojecting each 4 projections





Inverse Finite Radon Transform iFRT:

summing backprojections :

$$S = a + b + c + d + e + f + g + h + i$$

Almost same equation than Servières for Mojette Andrew Kingston & Imants Svalbe

S	S	S
+3a	+3b	+3c
S	S	S
+3d	+3e	+3f
S	S	S
+3g	+3h	+3i

Mojette Tomographic scheme



Mojette projection to Finite Radon Transform:

just summing bins every p bin:



Mojette-FRT Tomographic scheme



3. Links between Mojette, Fourier and FRT transforms

3.1 Links between Mojette and Finite Radon transforms

3.2 Links with the Fourier Transform3.1 Central Slice theorem3.2 Discrete rotations

Ph.D. Henri Der Sarkissian 2015

(1,2) 6 Lena image before rotation(21)



Ph.D. Henri Der Sarkissian 2015

Interpolation stage after rotation(2 1) 1 $(-\mathbf{p}_{\theta}, -\mathbf{q}_{\theta})$ 11 12 1 11 $(\mathbf{q}_{\theta}, -\mathbf{p}_{\theta})$ 12 12 12 8 11 1 11 12 4 1 $1 \text{ if } 2x \le ||p| - |q||$ $\frac{-2x + |p| + |q|}{2\min\{|p|, |q|\}} \text{ if } ||p| - |q|| < 2x < |p| + |q|$;) = • $(-\mathbf{q}_{\theta}, \mathbf{p}_{\theta})$ $(\mathbf{p}_{\theta}, \mathbf{q}_{\theta})$ 154

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Original 32x32

rotation(2 1)

interpolation in Mojette space



Nicolas Normand **Olivier** Philippé Florent Autrusseau **Benoit Parrein Pierre Evenou Pierre Verbert Myriam Servières Andrew Kingston Imants Svalbe** Chuanlin Liu **Aurore Arlicot** Henri Der Sarkissian

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KEOSYS Medical Imaging

Jerome Fortineau



XRozoFS

Pierre Evenou

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The Mojette Transform

Theory and Applications

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