

CASA Overview and Main Features (w/emphasis on VP/PB & A-Proj. implementation)

- Implements Measurement Equation (Hamaker, Bergman & Sault, 1996; later extended by Noordam & Cornwell) (see next page)
- Internal data format is Measurement Set (Kemball & Wieringa, 2000); Table for radio telescope data (visibilities) & auxilliary sub-tables; CASA Tables
- 1.5 Million lines of Code (Mostly C++)

User interface, higher-level analysis routines, viewers = Casa non-Core

- Tools: data access, display, science analysis

Examples:

• Simulator tool: simulator.xml, Simulator.cc (C++ Class)

python> sm.setvp(dovp=T, usedefault=F, ...): turn on/implement VP/PB for simulation
→ programmable command-line interface & scripting: Python (augmented by IPython)

• imager tool: imager.xml, Imager.cc, Imager2.cc
ftmachine = 'pbwproject'

- Tasks → high-level (user-level) analysis procedures:

• Tasks (implemented in Python) → Tools (implemented in C++)

• clean (python, xml): task-clean.py, clean.xml, cleanhelper.py

→ gridmode = 'aprojection' → (type of gridding kernel for FFT-based Transforms)
→ ftmachine = 'pbwproject'

Primary Beam correction (image domain, A-Projection)

python> im.setoptions(ftmachine = 'pbwproject')

clean(vis=msname, imagename=nameimag, mode='mfs', gridmode = 'aprojection', ...)



General physical & astronomical utilities, infrastructure = CASACore

Examples:

- MeasurementSets(.h) module handles storage of telescope data and access to it.
MeasurementSet is class that gives access to data.

- MSSimulator: Create empty MeasurementSet from observation and telescope descriptions.

• Simulator refers to generation of 'fake' data from set of parameters for instrument and sources. The application "simulator" uses this class to create a true simulated MS with perfect or corrupted data

CASA Measurement Equation → CASA C++ Classes and Modules

- Toolkit for radio astronomical calibration, imaging, & simulation built around Measurement Equation

observed Visibility

Antenna VP, i.e., PB effects

geometry

$$\vec{V}_{ij} = \vec{M}_{ij} \vec{B}_{ij} \vec{G}_{ij} \vec{D}_{ij} \int \vec{E}_{ij} \vec{P}_{ij} \vec{T}_{ij} \vec{F}_{ij} S \vec{I}_v(l, m) e^{i 2 \pi (u_{ij} l + v_{ij} m)} dl dm + A_{ij}$$

VisEquation C++ Class

Visibility-Plane effects
(Direction independent effects; const. across F.O.V.)

$$J_{ij}^{vis}(v, t) = M_{ij} B_{ij} G_{ij} D_{ij}$$

Image-plane or sky-plane part
(Direction-Dependent Effects)

SKYEquation C++ Class

$$J_{ij}^{sky}(v, t) = E_{ij} P_{ij} T_{ij} F_{ij}$$

Image to be derived
SKYModel C++ class

Additive baseline-based error component.

FTMachine

CubeSKYEquation C++ Class

Imager2.cc

nPBWProjectFT C++ Class

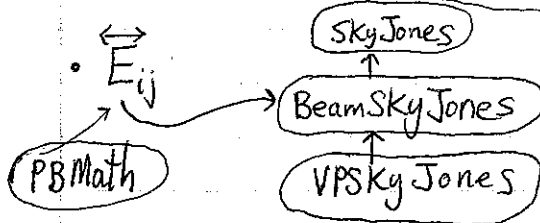
implements A-projection algorithm

fpbwproject.f (Fortran): gridding convolution function used by underlying gridded

IlluminationConvFunc, ConvolutionFunction C++ Classes

used to compute convolution functions for convolutional gridding

VLAilluminationConvFunc C++ class: computes autocorrelation of ideal antenna illumination pattern for VLA imaging.



- Classes that handle Fourier Transform part of M.E. (e.g., SKYEquation) use FTMachine (including nPBWProjectFT when A-projection is implemented) to carry out forward and inverse Fourier transforms.

- i, j = telescope I.D. pairs = baseline

CASA Imaging & Deconvolution (with and without Direction-Dependent Effects (DDEs)).

- Imager.cc, Imager2.cc: CASA C++ classes that contain functions needed for the imager tool.
- imager (imager.xml): Tool that accomplishes synthesis processing.
- clean task (clean.xml, cleanhelper.py, clean-pg.py): Can set 'gridmode' parameter (to, e.g., 'aprojection') and ftmachine (to, e.g., 'pbwproject') here.
- Clark CLEAN algorithm can be implemented via ClarkCleanLatModel and ClarkCleanImageModel C++ classes (for example)

* Classical/Traditional Description of Imaging & Deconvolution without Consideration of DDEs: Linear Optimization View of Deconvolution

- Measurement Equation Describing Interferometer can be written as

$$\vec{V}^0 = [A] \vec{I}^0 + \vec{N} \quad (1), \quad \text{where}$$

\vec{V}^0 = true visibilities

$[A]$ = measurement matrix operator: linear transformation from image to visibility domain

\vec{I}^0 = true image (vector)

\vec{N} = Gaussian random variable (in data domain), or, independent random noise vector.

- Model visibilities (\vec{V}_{ij}^M) for baseline i-j are calculated from existing model image \vec{I}^M :

$$\vec{V}^M = [A] \vec{I}^M \quad (2), \quad \text{where}$$

$$\vec{I}^M = \sum_k P_k, \quad P_k = \text{Pixel Model} = F_k \delta(x-x_k, y-y_k) = \left\{ \begin{array}{l} \text{collection of delta} \\ \text{functions of amplitude} \\ F_k \text{ at each pixel location} \end{array} \right\}$$

- χ^2 is optimal estimator

- Generalized dirty image is update direction for iterative deconvolution:

$$\Delta \vec{I}^{\text{dirty}} = -C \Delta \chi^2, \quad \text{where } \rightarrow$$

$$\chi^2 = |\vec{V}^o - [A] \vec{I}^M|^2, \quad C = \text{covariance matrix}$$

Note: $\frac{\partial \chi^2}{\partial P_k} \equiv [\text{Dirty Image}]$

Typically, model image is iteratively improved as:

$$\vec{I}_i^M = T(\vec{I}_{i-1}^M, [\vec{I}_i^R]) = \vec{I}_{i-1}^M + \alpha \text{map}[\Delta \vec{I}_i^{\text{dirty}}] \quad (3)$$

$$\rightarrow \vec{I}_{i-1}^M + \alpha \Delta \chi^2 \quad (\text{where } 0 < \alpha < 1),$$

where

$$\Delta \vec{I}^M = [\text{update to existing model image}] = -C' \frac{\partial \chi^2}{\partial \vec{I}^M}, \quad (C' = \text{scaling term, either const. or inverse of Hessian})$$

$$\vec{I}_i^R = \mathcal{F}\{\vec{V}^R\} \equiv \text{FT}\{\vec{V}^R\} \equiv (\text{Fourier transform of } \vec{V}^R),$$

where residual visibilities $\vec{V}^R = \vec{V}^{\text{obs}} - \vec{V}^M$, \vec{V}^{obs} = observed visibilities

\vec{I}_i^M = cumulative model of i th iteration

T = operator that selects part of gradient image and includes conversions between signal domain, polarization domain, and stokes frame using appropriate transform operator.

- Major Cycle can be broken down into two calculations:

(1) Forward: In forward step, model visibilities (V_{ij}^M) for baseline $i-j$ are calculated from existing model image \vec{I}^M , using Eq. (2).

• When using FFT algorithm for computing Fourier Transform, gridded visibilities are interpolated from regular grid and re-sampled at measured (u, v, w) points as

$$\vec{V}^M(u_{ij}, v_{ij}, w_{ij}) = ([G] \underbrace{[F \vec{I}^M]^g}_{\text{gridded visibilities}})(u_{ij}, v_{ij}, w_{ij}) \quad (4), \quad \text{where}$$

$[G]$ = interpolation operator

$[F]$ = Fourier Transform operator

g : indicates data on a regular grid

(2) Backward: In backward calculation, residual visibilities $\vec{V}^R = \vec{V}^{\text{obs}} - [A] \vec{I}^M$ are propagated backwards to image plane using \rightarrow

$$\vec{I}^R = [A^T A]^{-1} A^T \vec{V}^R = FT[\vec{V}^R] = [\text{residual image}] \quad (5)$$

- When using FFT algorithm for computing FT, backward calculation will correspond to application of $[GF]^T$ (see Eq. (4)), where operator $[F]$ is unitary.
- If $[G]$ is at least approximately unitary, $[G]^T$ can be used as interpolation operator for re-sampling data on a regular grid to correct for effects of $[G]$ in image.
- An approx. inverse operator with finite support for our purposes can be constructed by using G^T for re-sampling data (l.h.s. of Eq. (4)) and then dividing resulting image by $\det(FG)$.

⊗ Imaging and Deconvolution with D.D.E. (including use of A-Projection Algorithm)

- Recall that full Measurement Equation can be written as:

$$V_{ij}^{\text{obs}}(v) = \underset{\substack{\uparrow \\ \text{Data}}}{J_{ij}^{\text{vis}}(v,t)} \int \underset{\substack{\uparrow \\ \text{Corruptions}}}{J_{ij}^{\text{sky}}(s,v,t)} I(s,v) \underset{\substack{\uparrow \\ \text{sky (Image)}}}{e^{i\vec{s} \cdot \vec{b}_{ij}}} \underset{\substack{\uparrow \\ \text{geometry (w-term)}}}{d\vec{s}} \quad (6)$$

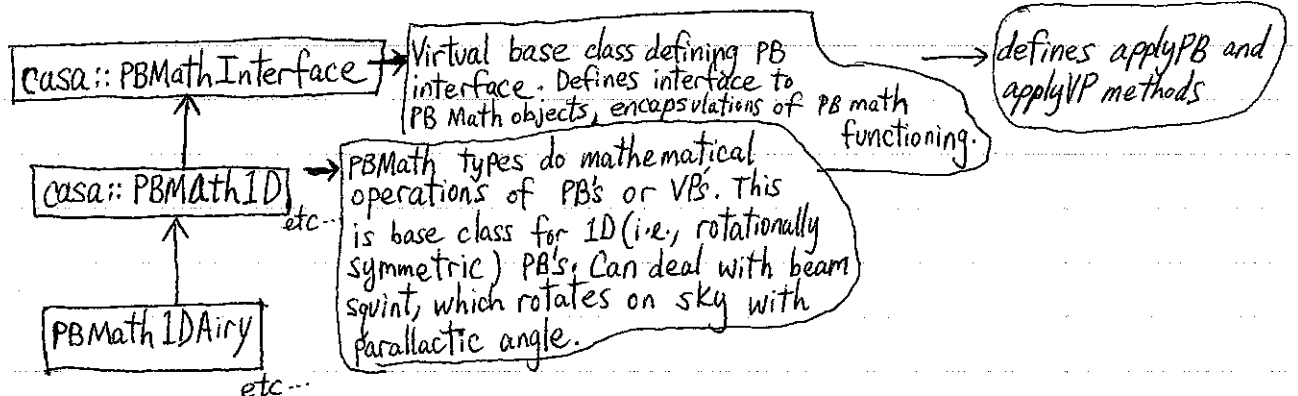
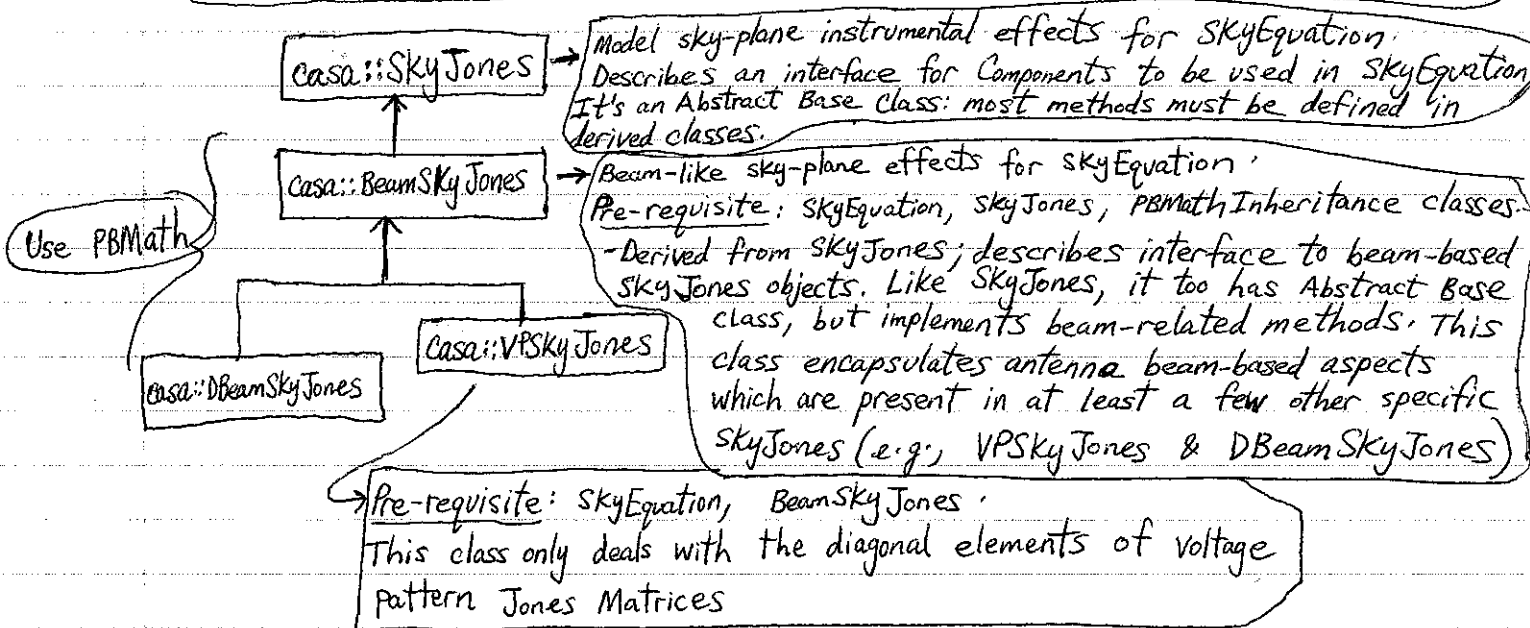
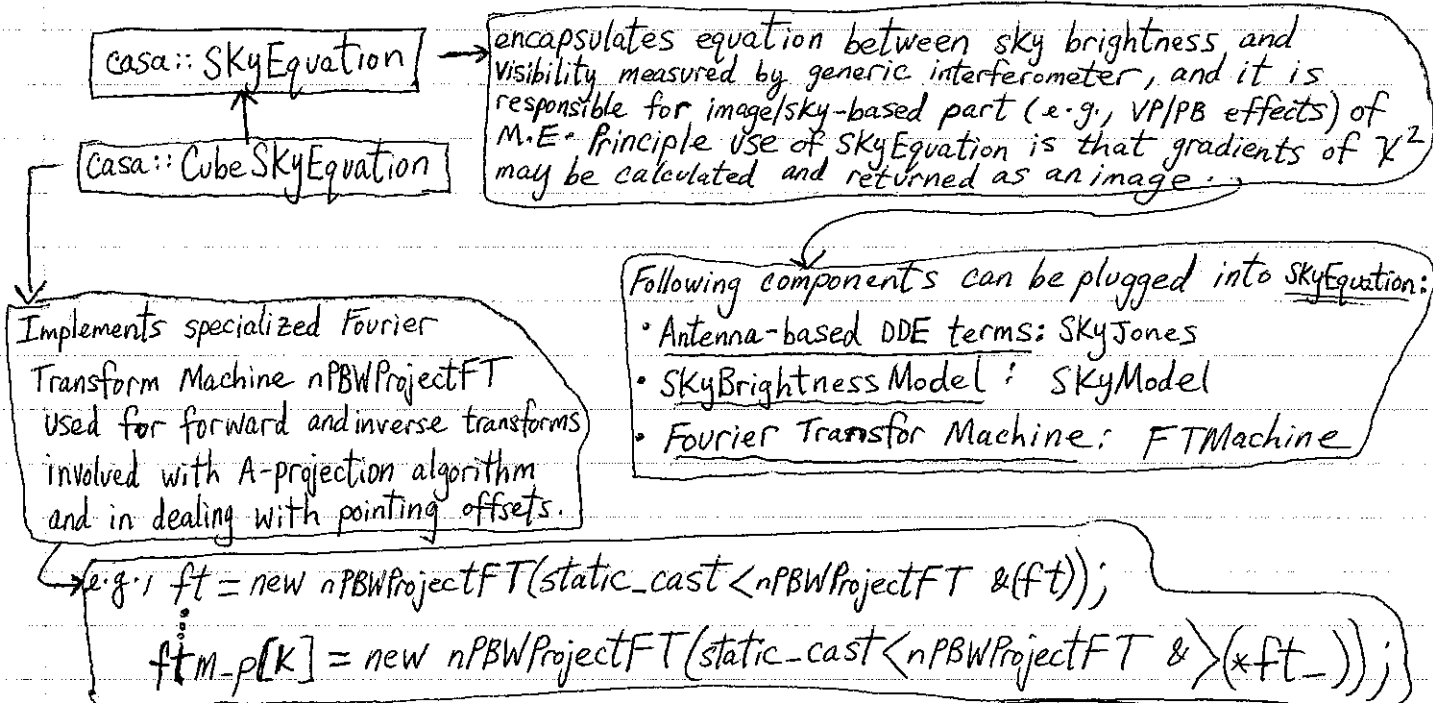
Where,

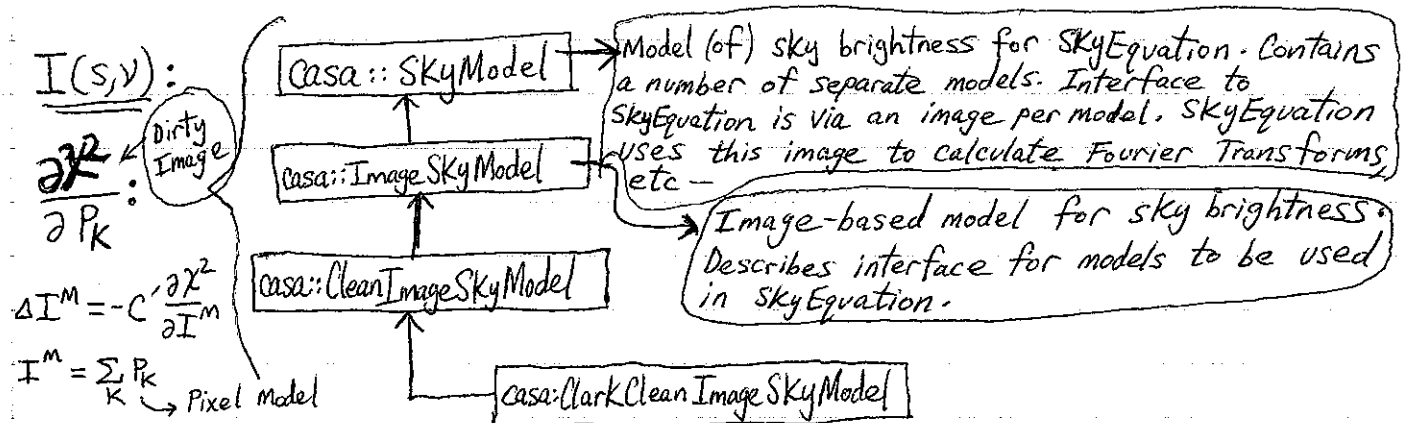
Direction Cosines: $\vec{s} = (l, m, n) = (l, m, \sqrt{1-l^2-m^2})$

Baseline Vector: $\vec{b}_{ij} = (u_i - u_j, v_i - v_j, w_i - w_j) = (u_{ij}, v_{ij}, w_{ij})$

- $J_{ij}^{\text{vis}} = J_i^{\text{vis}} \otimes J_j^{\text{vis}}$ (Direction independent effects; const. across F.O.V.): handled by CASA C++ class VisEquation \Rightarrow Visibility Measurement Equation expressing visibility-plane part of M.E.; Pre-requisite: MeasurementComponents module
- $J_{ij}^{\text{sky}} = J_i^{\text{sky}} \otimes J_j^{\text{sky}}$ (Direction-Dependent Effects; e.g., Antenna PB): Image-Plane or sky-Plane part of M.E., handled by CASA C++ classes skyEquation as well as CubeSkyEquation, BeamSkyJones, VPSkyJones, PBMath, PBMath1D, etc ---

Relevant C++ Inheritance Diagrams:





- A-Projection Algorithm:

- An approximately unitary operator E_{ij} can be constructed as FT of full direction-dependent SKY Mueller Matrix J_{ij}^{sky} ,

$$E_{ij} = FT[J_{ij}^{sky}] \quad (7)$$

\Rightarrow Image plane corrections can be incorporated as part of deconvolution process by using E_{ij} and E_{ij}^+ as part of forward and backward (reverse) transforms between visibility and image domains for baseline $i-j$.

In absence of antenna pointing errors, operator E_{ij}^P is auto-correlation of ideal antenna illumination patterns of polarization product P . In presence of antenna pointing errors, E_{ij}^P is different for each baseline $i-j$.

- Now, can re-write $M \cdot E$ (Eq. (6)) as (simplified):

$$V_{ij}^{obs} = E_{ij}^P * [V^0] = E_i^{*P} * E_j^P * [V^0] \quad (8), \text{ where}$$

$$E_i^P = \text{Antenna Aperture Illumination Pattern} = FT[J_i^{sky}]$$

- Here V^{obs} is equal to the true visibilities V^0 convolved with autocorrelation of antenna aperture illumination pattern.
- In backward application of DDEs, conversion from image plane to $u-v$ plane involves application of DDE's to predicted visibilities. This can be realized by

using E_{ij}^{PT} as an interpolation operator for re-sampling $V^P(u_{ij}, v_{ij})$ (visibilities for polarization product P) on regular grid at pixels by indices (n, m) as:

$$V^{P,G}(n\Delta u, m\Delta v) = (E_{ij}^{PT} V^P(u_{ij}, v_{ij}))(n\Delta u, m\Delta v) \quad (9), \text{ where } G \text{ is used to indicate on a regular grid.}$$

- In forward application of DDE's (converting from uv plane to image plane, i.e., imaging), DDE's are applied by means of convolution during uv-plane gridding stage, and images corresponding to gridded visibilities are then computed as

$$I^{\text{dirty}} = \det(F^T [E_{ij}^{PT}])^{-1} F^T V^{P,G} \quad (10)$$

We can also describe and explain Eqs. (9) & (10) using following notation and in following way:

If there exists a function K_{ij} such that $K_{ij}^T * E_{ij} \sim \text{Delta Function}$, then:

$$\text{- Gridding: } V_{ij}^G = K_{ij}^T * V_{ij}^{\text{obs}} = K_{ij}^T * E_{ij} * [V^0] \approx [V^0]_{ij} \quad (11)$$

$$\text{- Imaging: } \text{FFT}[V^0] \rightarrow I^{\text{dirty}} \quad (12)$$

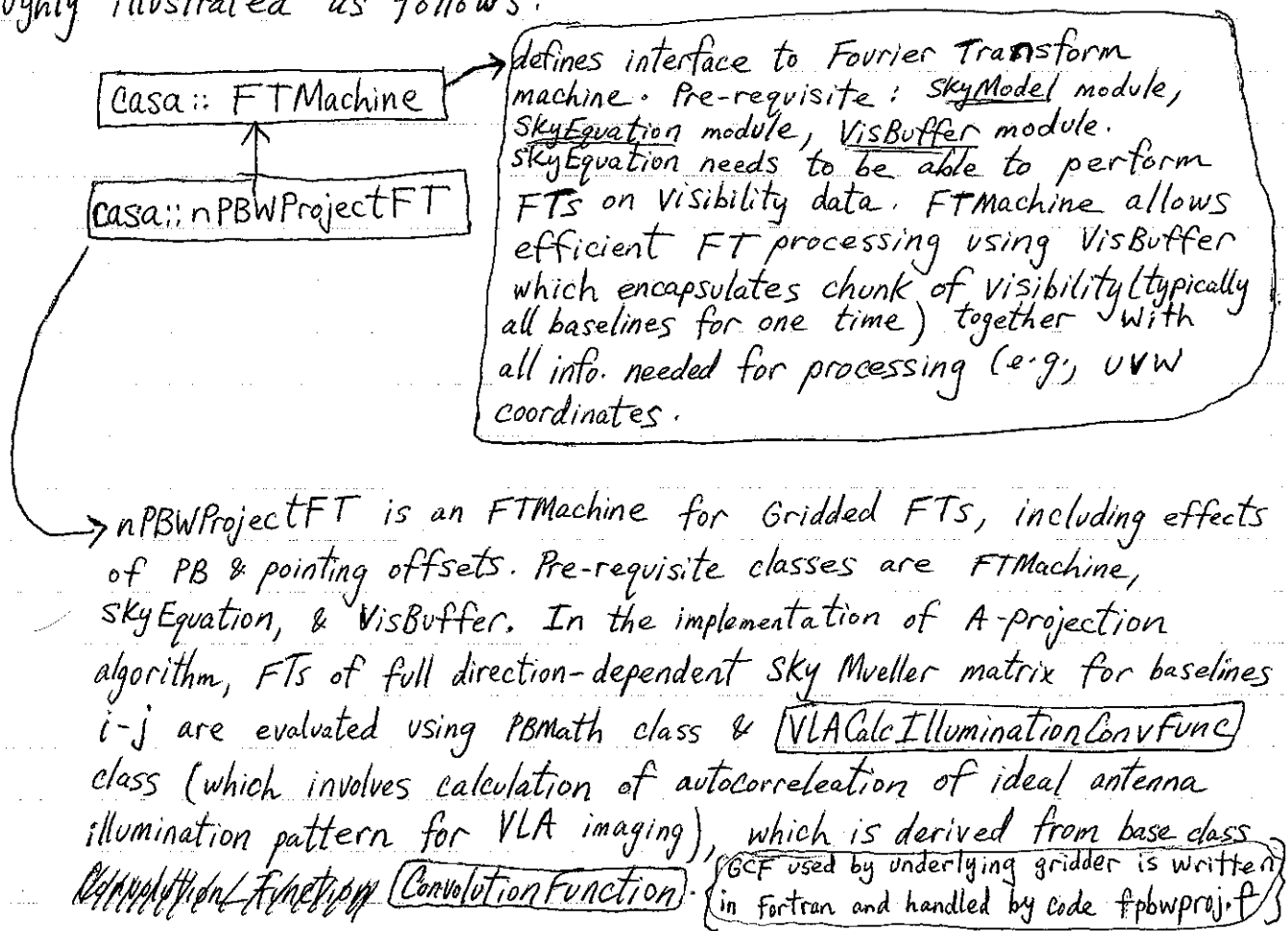
$$\text{- Prediction: } V_{ij}^M = K_{ij} * \text{FFT}[I^M] \quad (13)$$

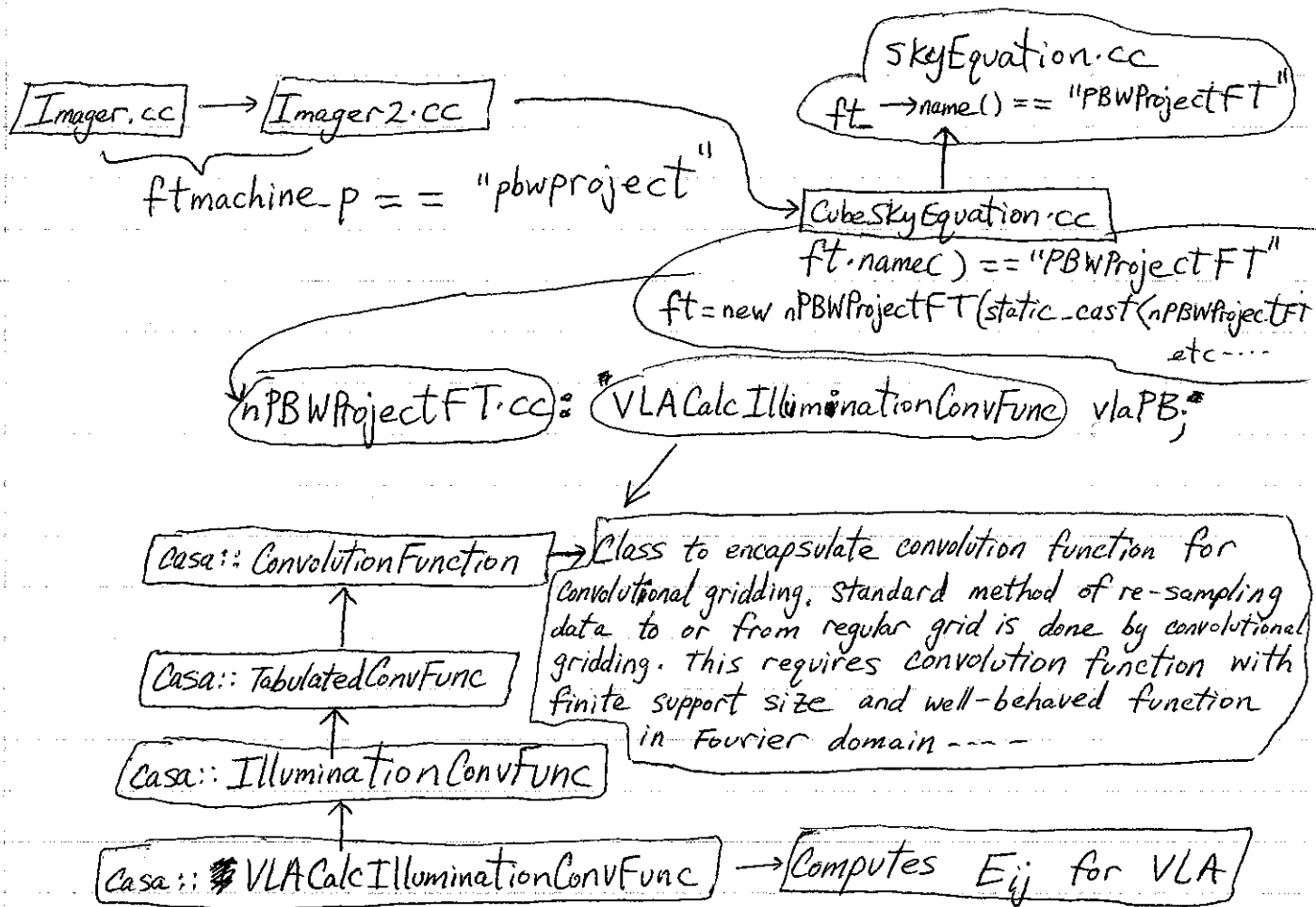
A-Projection provides accurate method to apply known DDEs in forward direction, during de-gridding step, when predicting visibilities from a model image, and approximate method to correct for them in reverse direction (when gridding visibilities for imaging).

Overall Deconvolution Algorithm with A-Projection can be summarized as follows:

- ① Initialize: Set initial model to 0 or to model using apriori knowledge of sky emission (e.g., model obtained with conventional techniques).
- ② Major Cycle
 - Forward Calculation: Compute residual visibilities $V^{obs} - V^M$ using observed visibilities V^{obs} for each polarization product.
 - Backward Calculation: Compute residual image using Eqs. (9) & (10) above.
- ③ Minor Cycle: Update model image applying some operator T (see Eq. (3)).
- ④ Go to ② until convergence reached, typically quantified by suitable stopping criteria (noise level, distribution of residuals, etc—)
- ⑤ Smooth deconvolved image by resolution element and add back residuals.

• In terms of CASA C++ Classes ~~///the/~~ and inheritance diagrams, implementation of A-Projection ~~in~~ in CASA can be roughly illustrated as follows:





References :

- A&A,
- Bhatnagar, S. et al., 1487, 419, 2008 ; EVLA Memo #100 (2006)
- Rav, U. et. al., Proc. IEEE, Vol. 97, No. 8, 2009
- Smirnov, O., A&A, 527, A107, 2011
- <http://www.aoc.nrao.edu/~sbhatnag>
- CASA Class Hierarchy: <http://casa.nrao.edu/active/docs/doxygen/html/hierarchy.html>