I-ImaS

Workpackage-3:

Update on current progress and report for deliverable D.8:
"Translating information signatures to a sequence of well-defined processing functions"

Oslo, 14^{th} – 15^{th} February 2005

Harris Georgiou (WP3/CTI)

WP3 tasks:

- √ **Task 3.1**: creation of an image database for medical applications
- √ **Task 3.2**: Identification of important features to be measured by the image analysis
- √ **Task 3.3**: Feature analysis and selection, in order to decide which features to use as feedback to the sensor system for different applications using the information from previous task
- ► **Task 3.4**: Evaluation of operator response to the images created by using selected features as feedback to the sensors

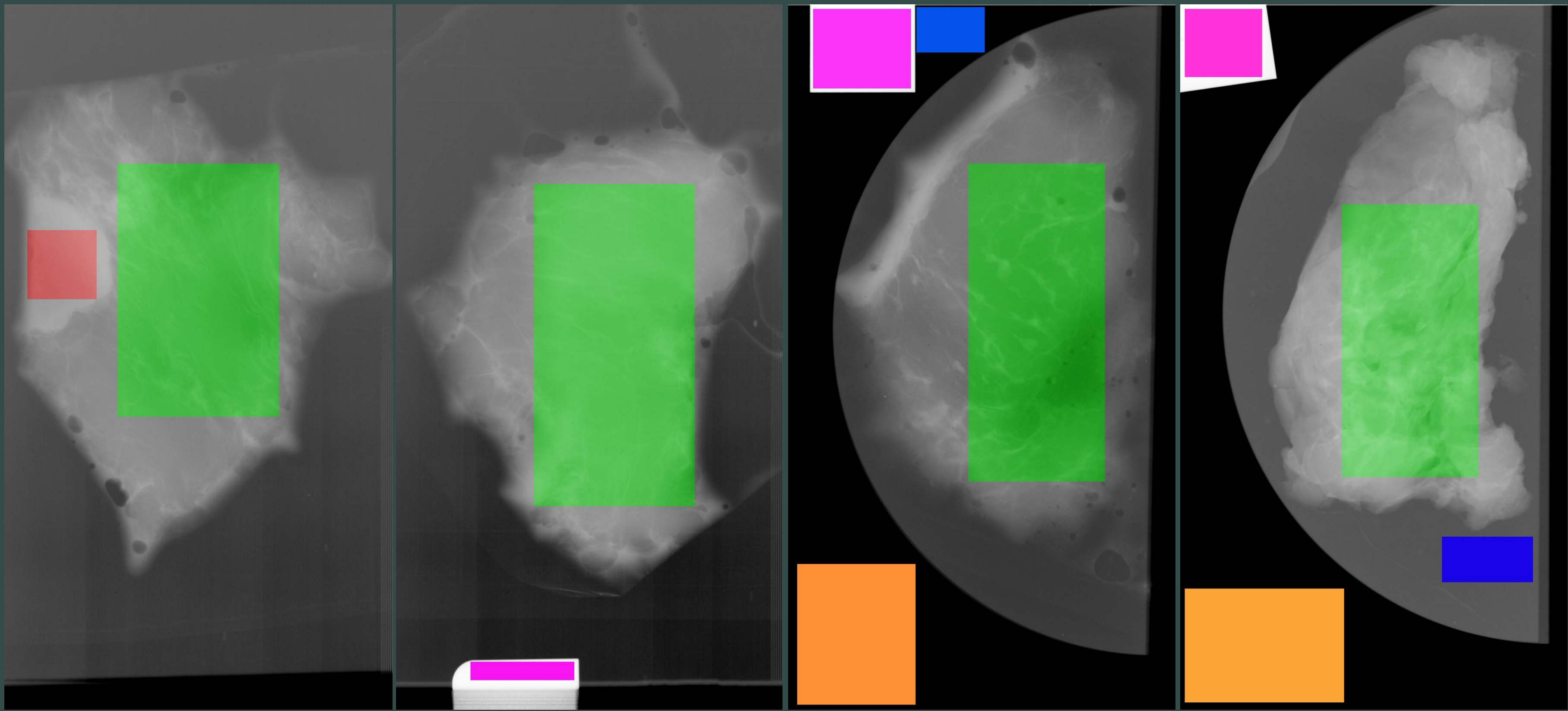
WP3 deliverables:

- √ **D.7**: An organized, searchable database of images from medical applications (Dec.2004)
- √ **D.8**: A report on the translation of the information signatures to a sequence of well-defined processing functions (Dec.2004) [23]
- ► **D.9**: A report summarizing the results of evaluating the different approaches to providing intelligence in the sensor/imaging system (Feb.2004)

Current Progress Overview:

- **D.8: overview of final conclusions**
- D.9: sensor IC intelligence options & implementation
- Further work & Proposals

Real breast tissue image database (DB3) – Overview



U01 U02 U03.02 U04.03

Real breast tissue image database (DB3):

- It is based on 4 different real breast tissue samples
- Exposed at different kVp and mAs settings
- Plastic wrapping could NOT be physically removed
- Resulting artifacts had to be evaluated against results

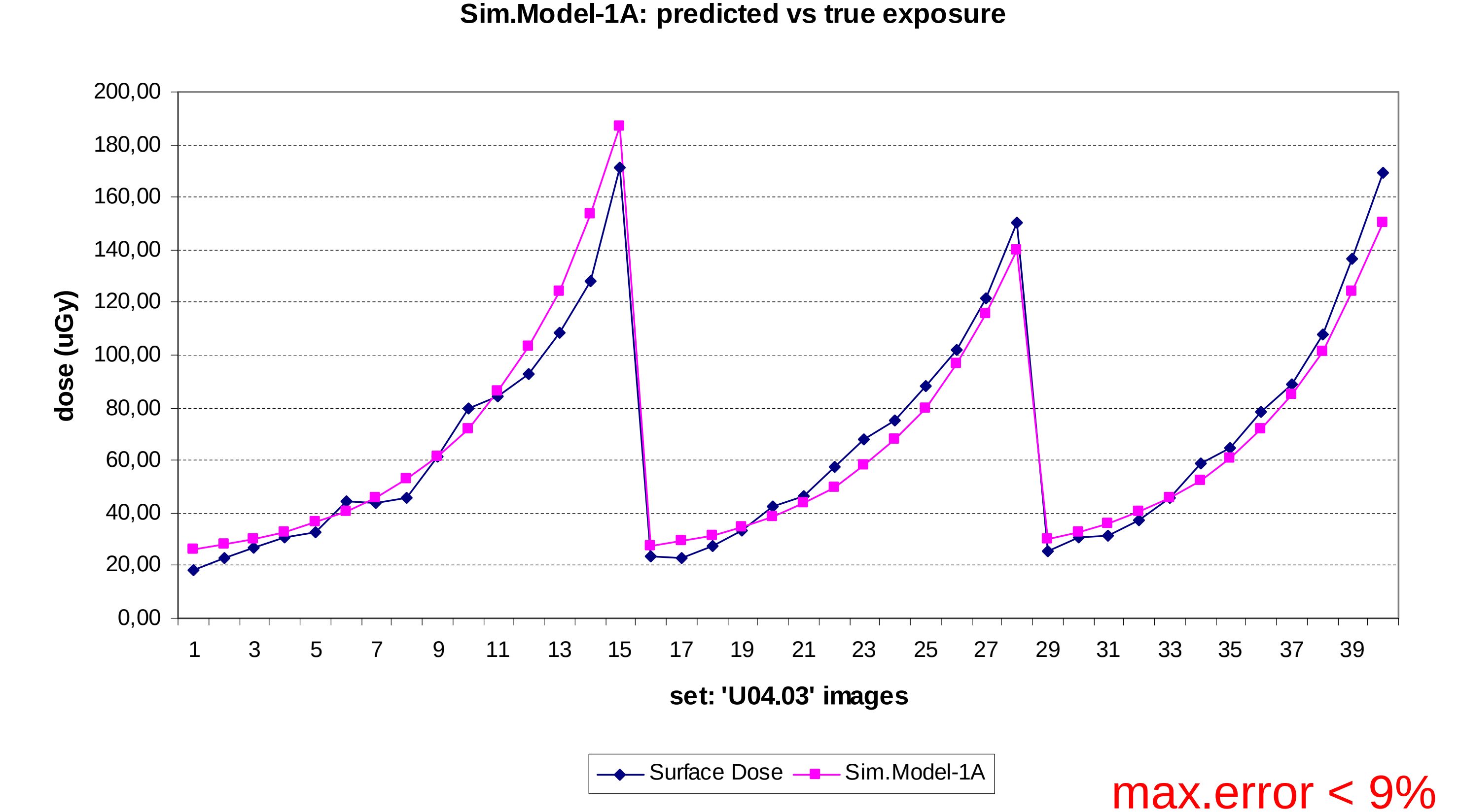
PredModel-2A/B: Textural Features Validation [23]

1. Confirm SimModel-1A results over exposure and OD
2. DB3: Global statistics, noise estimation, greyscale usage
3. Efficiency and stability of textural feature extractors (20)
4. Statistics: histogram pre-processing, image artifacts, etc.

Issue # 1: Confirmation of SimModel-1A [23]

(1a) Exposure level: estimation, adjustment, extrapolation

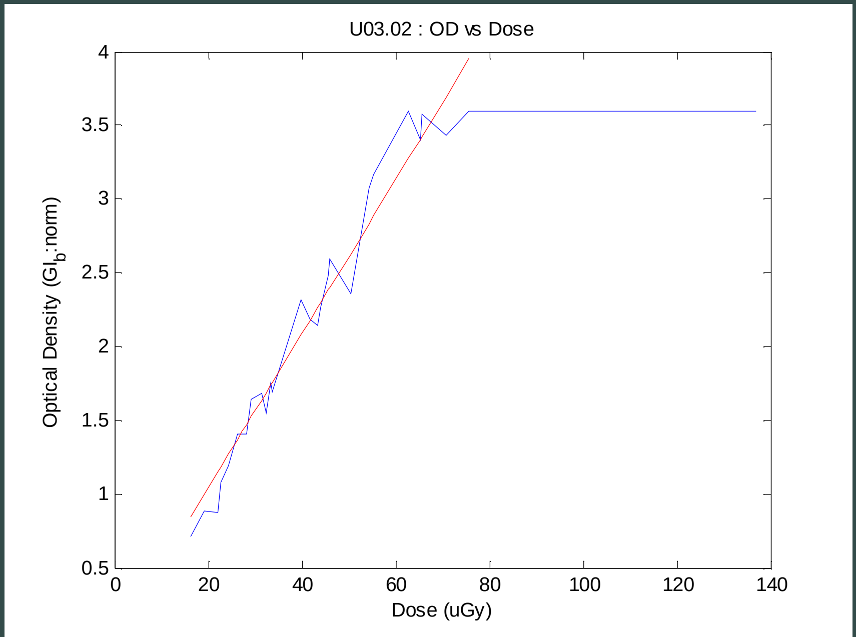
$$Rx: f_1(kVp, mAs) = C_{1,1} \cdot \log_{10}\{(kVp)^2 \cdot (mAs)\} + C_{1,0}$$

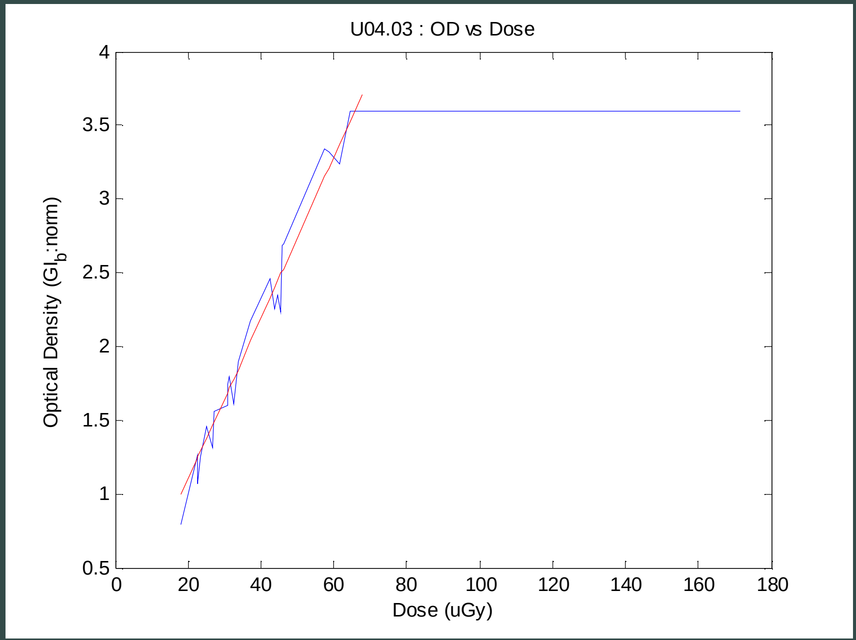


max.error < 9%

Issue # 1: Confirmation of SimModel-1A [23]

(1b) Optical Density: translation from exposure level

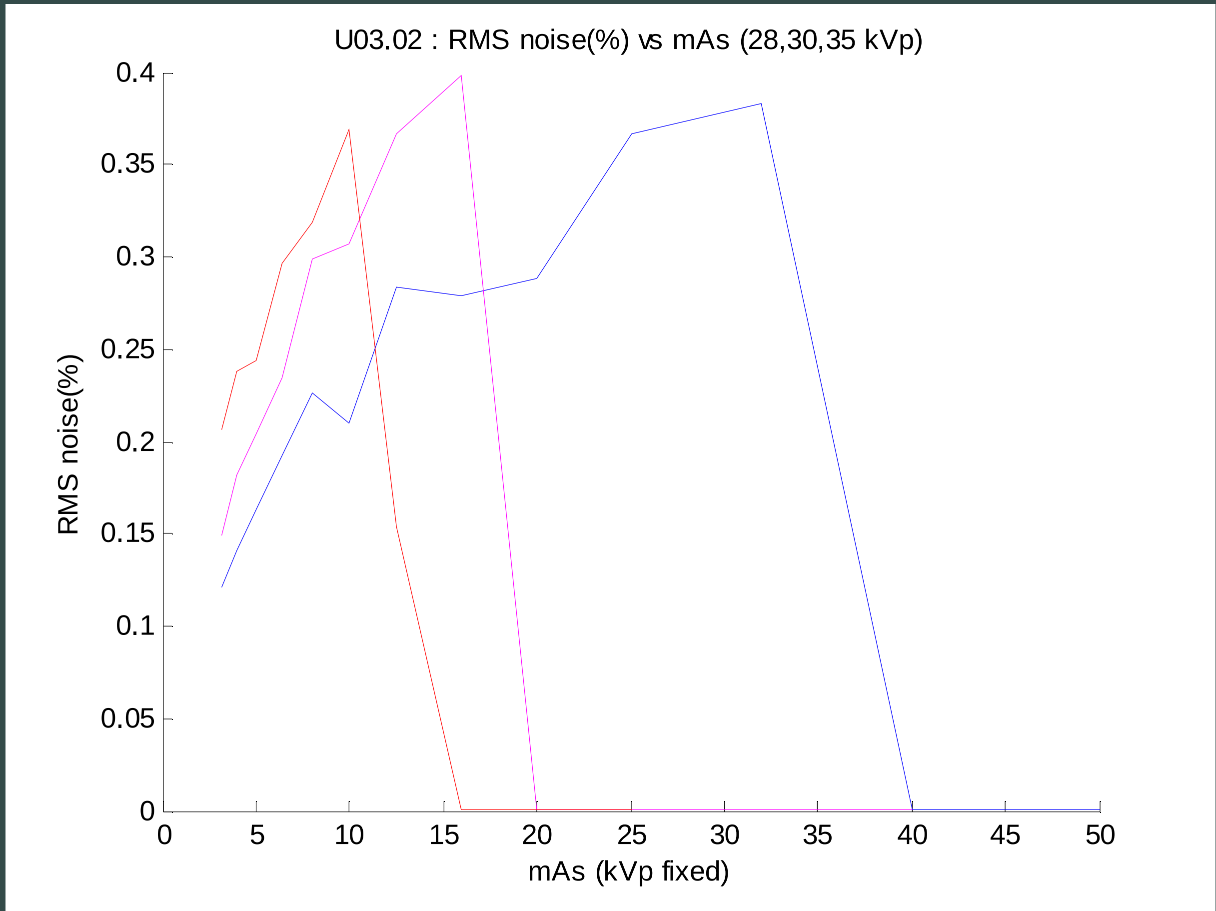




Resulting greyscale mapping: near-linear over non-saturated areas

Issue # 2: Global statistics on DB3 images

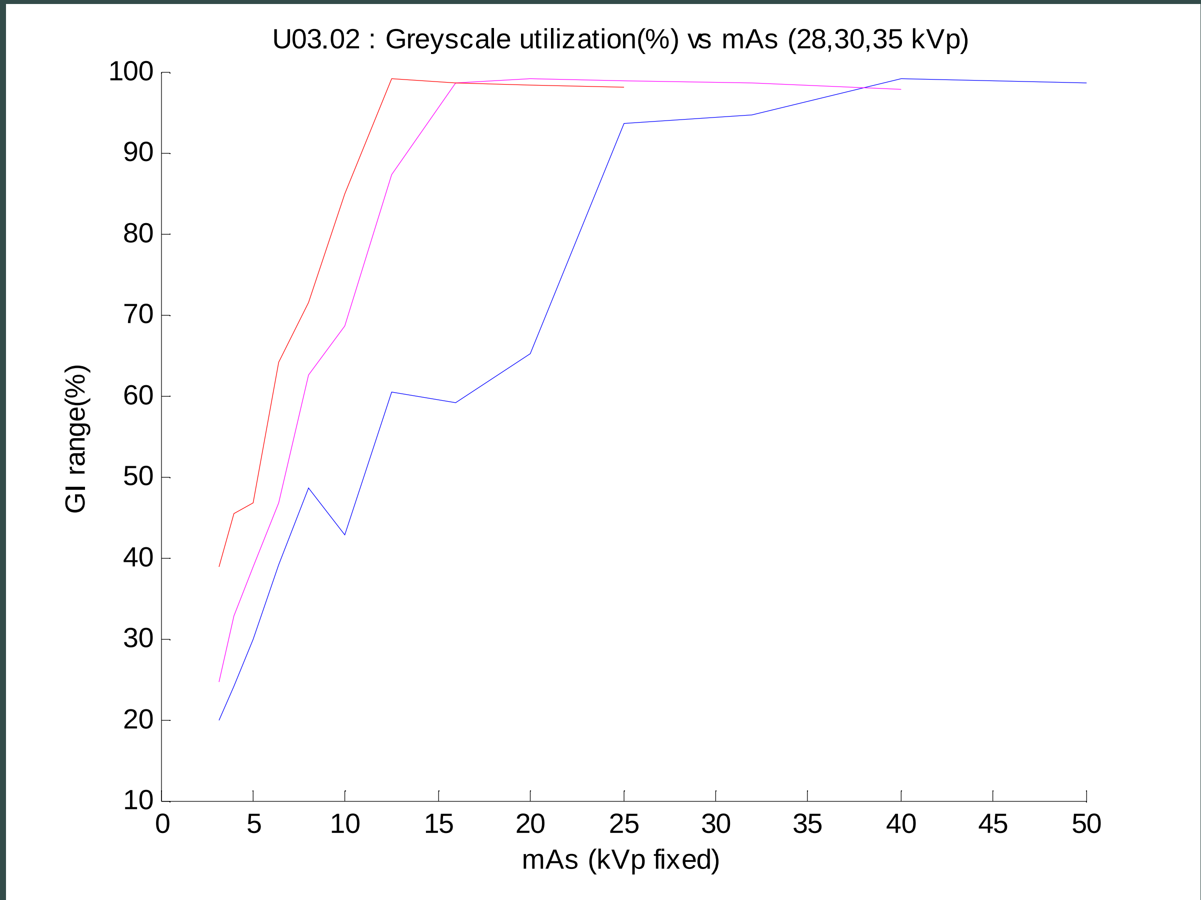
(2a) Noise over exposure: RMS% estimation from stdev



Stdev: increasing with kVp and mAs as expected over non-saturated areas

Issue # 2: Global statistics on DB3 images

(2b) Greyscale utilization over exposure level



GI.Range%: increasing with kVp and mAs as expected over non-saturated areas

Issue # 3: Texture "signatures" against exposure rates

PredModel-2A/B: Model Summary

- All 20 textural feature extractors were included during the analysis.
- Every feature function was evaluated comparatively against previous results.
- No cumulative column-wise averaging was used due to lack of orientation.
- Sampling box size was 50x50 pixels.
- Pre-processing: Gamma correction (logarithmic histogram rescaling)
- Response curves were calculated for different gamma correction levels.

Gamma correction levels used:

- nominal level (no rescaling): g = 1.00
- enhance black (log hist): g = 0.62
- enhance white (exp hist): g = 1.60

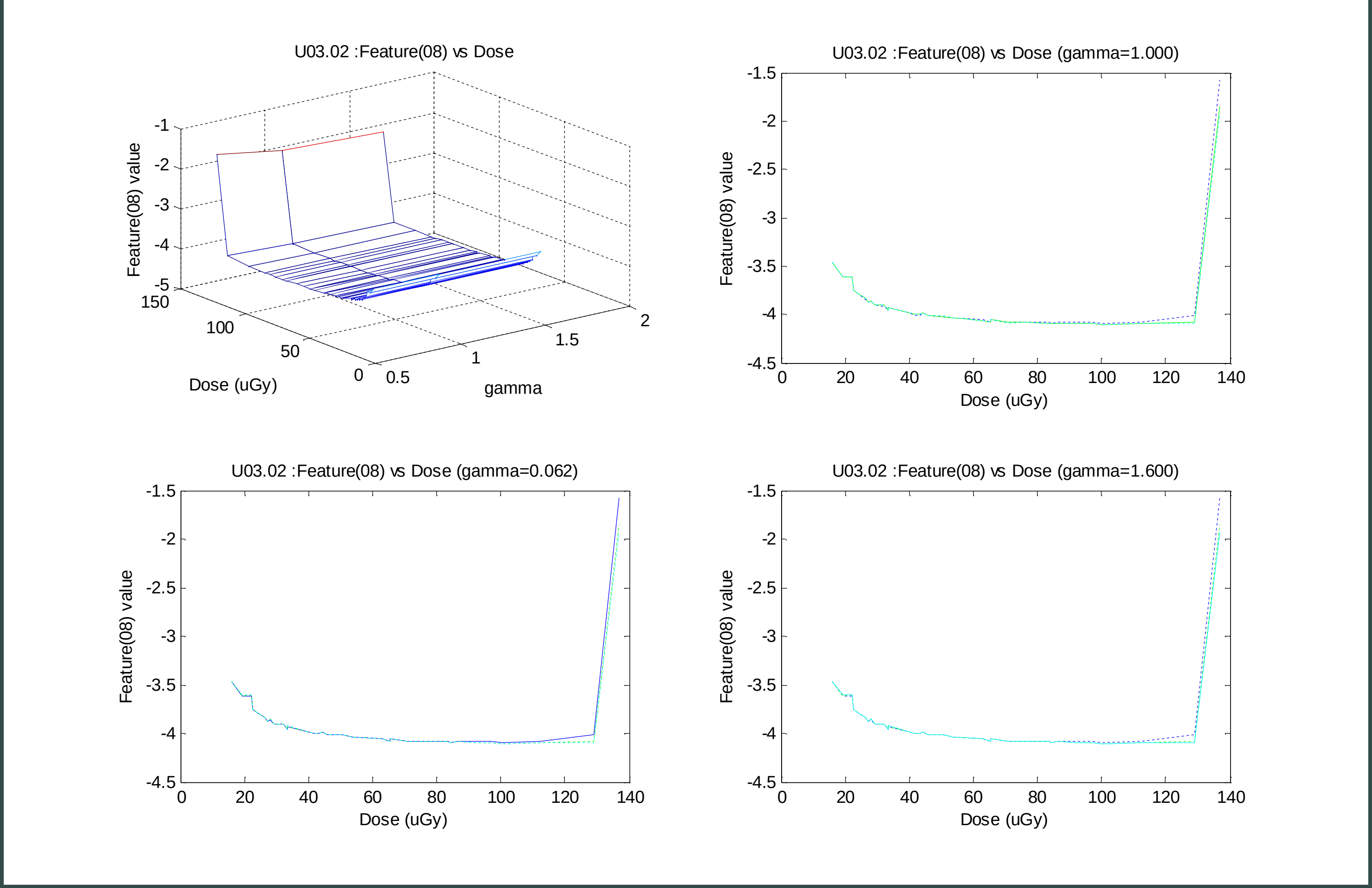
Rescalings: **± 11.6%** in brightness

Best feature functions so far:

- F01: "MIN"
- F02: "MAX"
- F03: "MEAN"
- F07: "POWER"
- F11: "VOLUME"
- SF19: (normalized power)
- SF20: (normalized exposure)

Issue # 3: Texture "signatures" against exposure rates

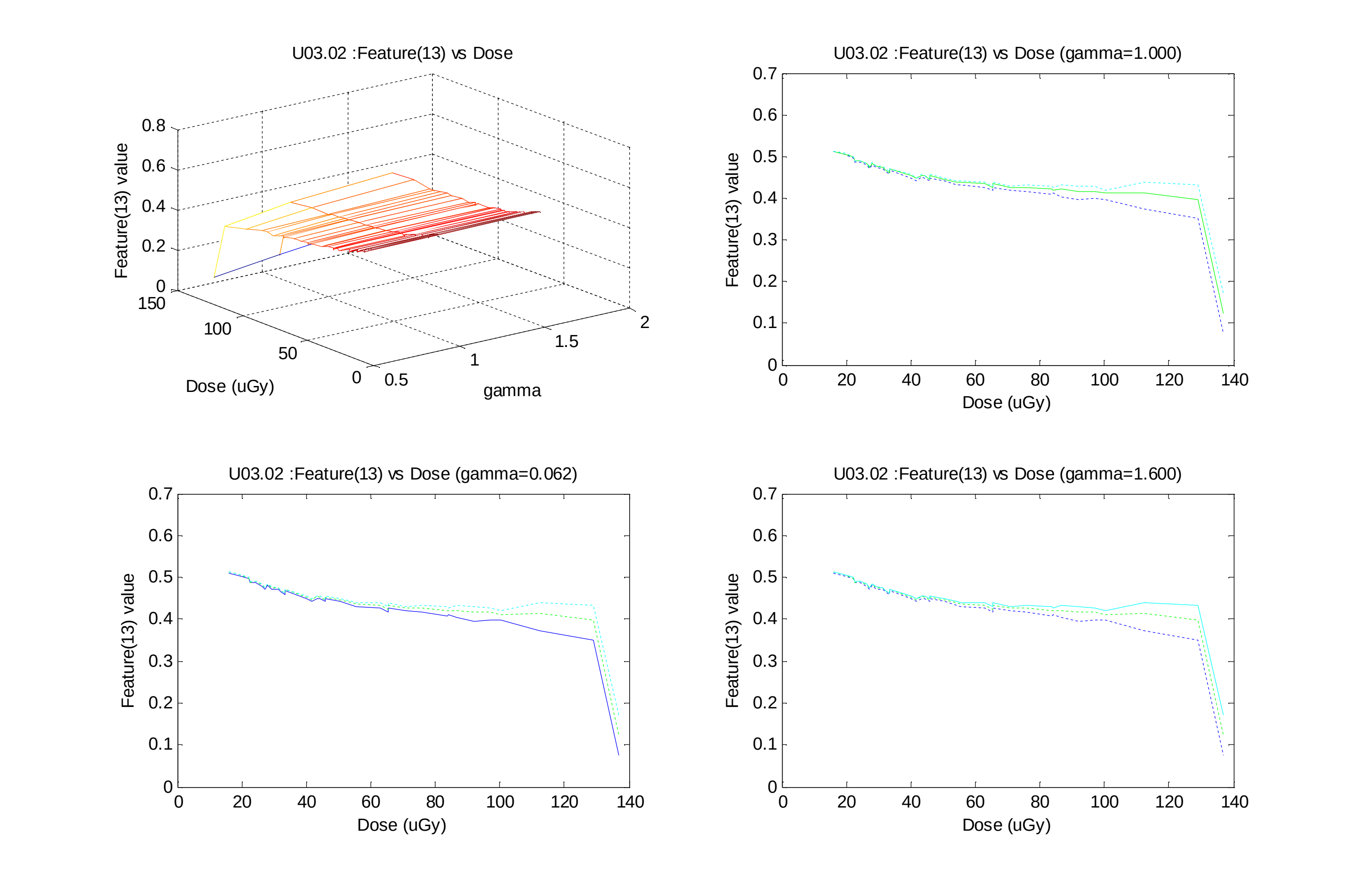
(3a) Example of BAD feature function response (not selected):



F08 (ENTROPY): response curve is "flat" for all gamma correction levels

Issue # 3: Texture “signatures” against exposure rates

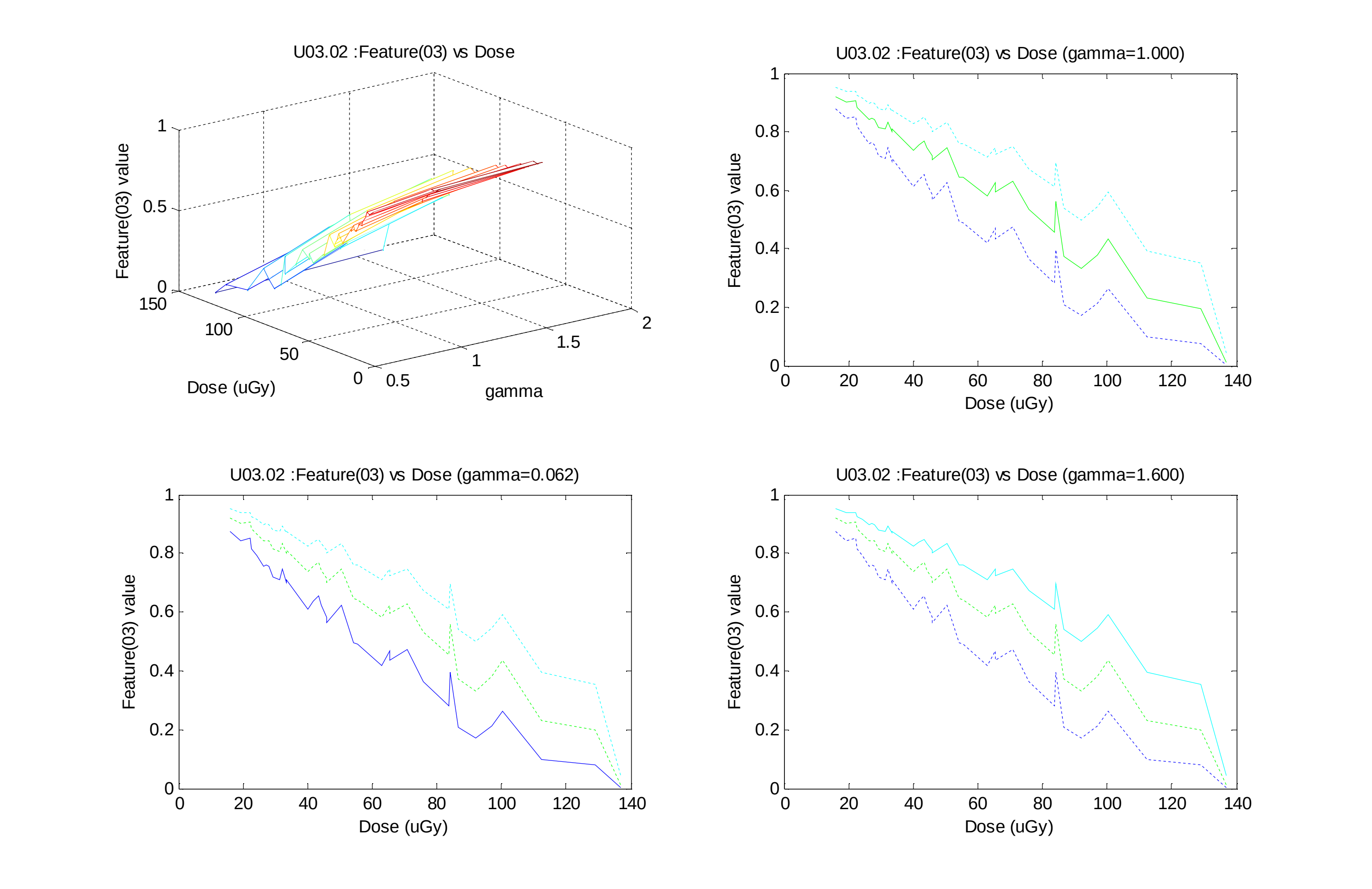
(3b) Example of BAD feature function response (not selected):



SF13 (synthetic): response curve is “flat” for all gamma correction levels

Issue # 3: Texture "signatures" against exposure rates

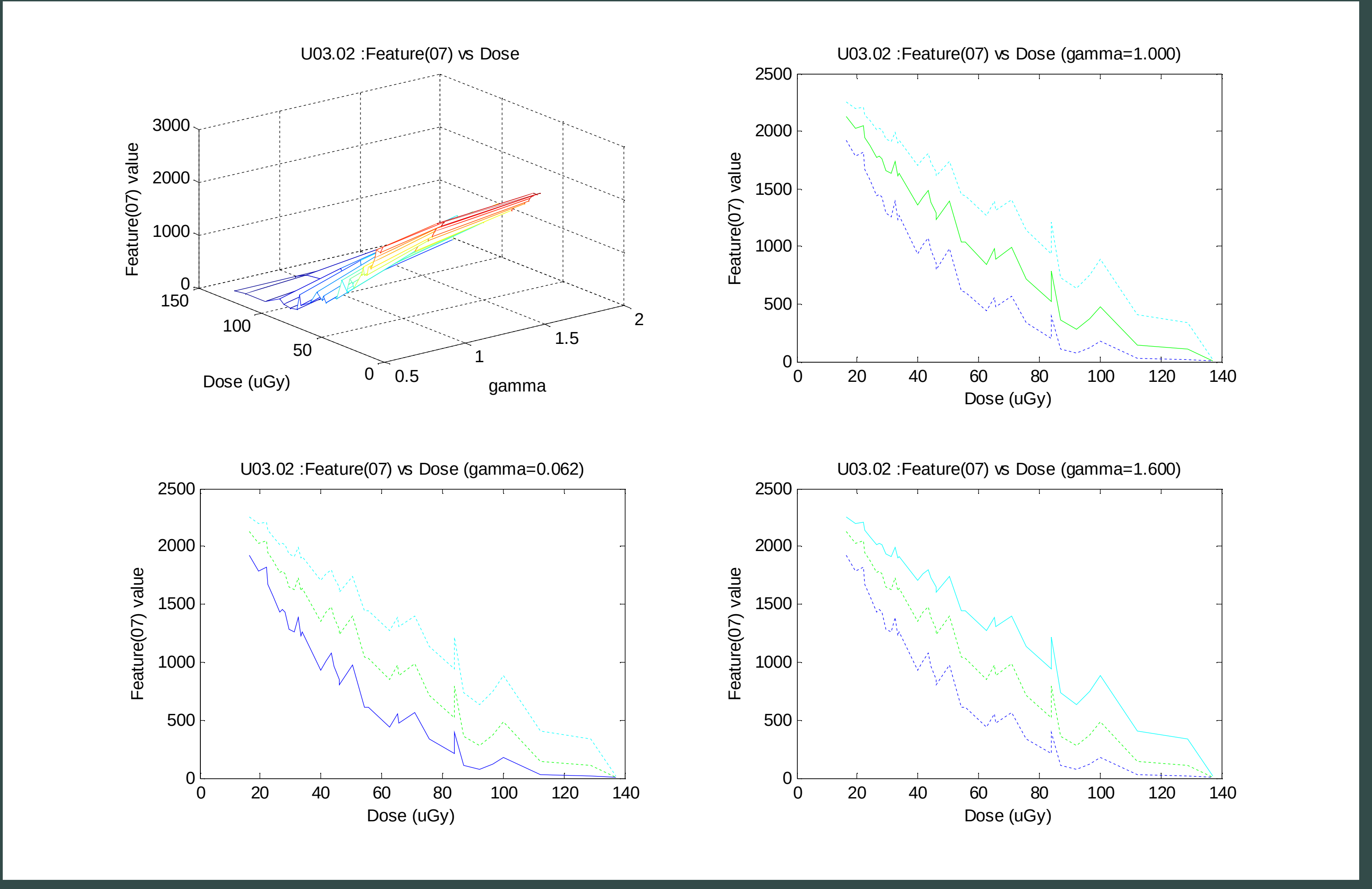
(3c) Example of GOOD feature function response (original set):



MIN, MAX, MEAN: response curve is near-linear & consistent for all gamma levels

Issue # 3: Texture "signatures" against exposure rates

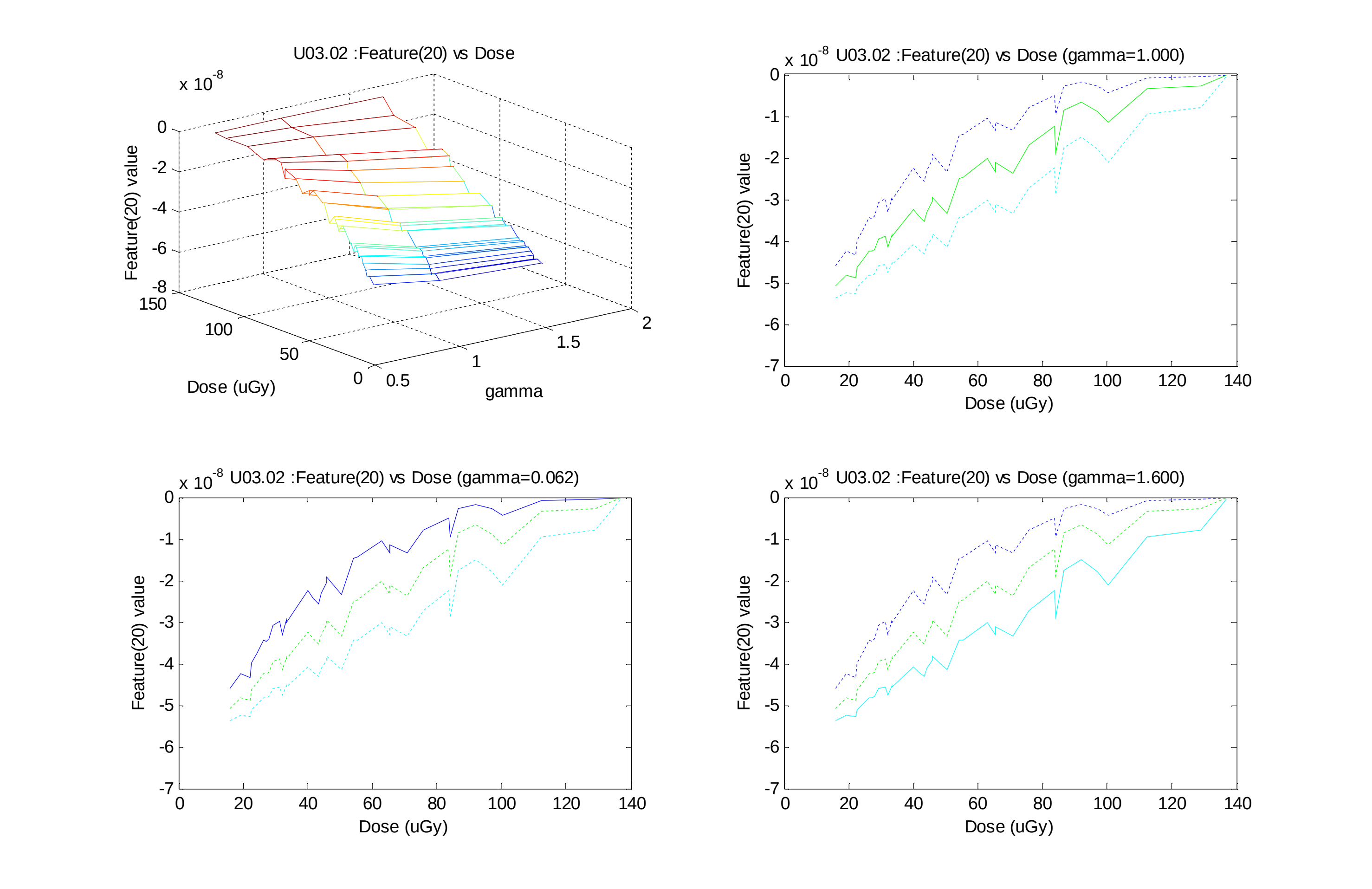
(3d) Example of GOOD feature function response (original set):



POWER, VOLUME, SF19: response is near-linear & consistent for all gamma levels

Issue # 3: Texture "signatures" against exposure rates

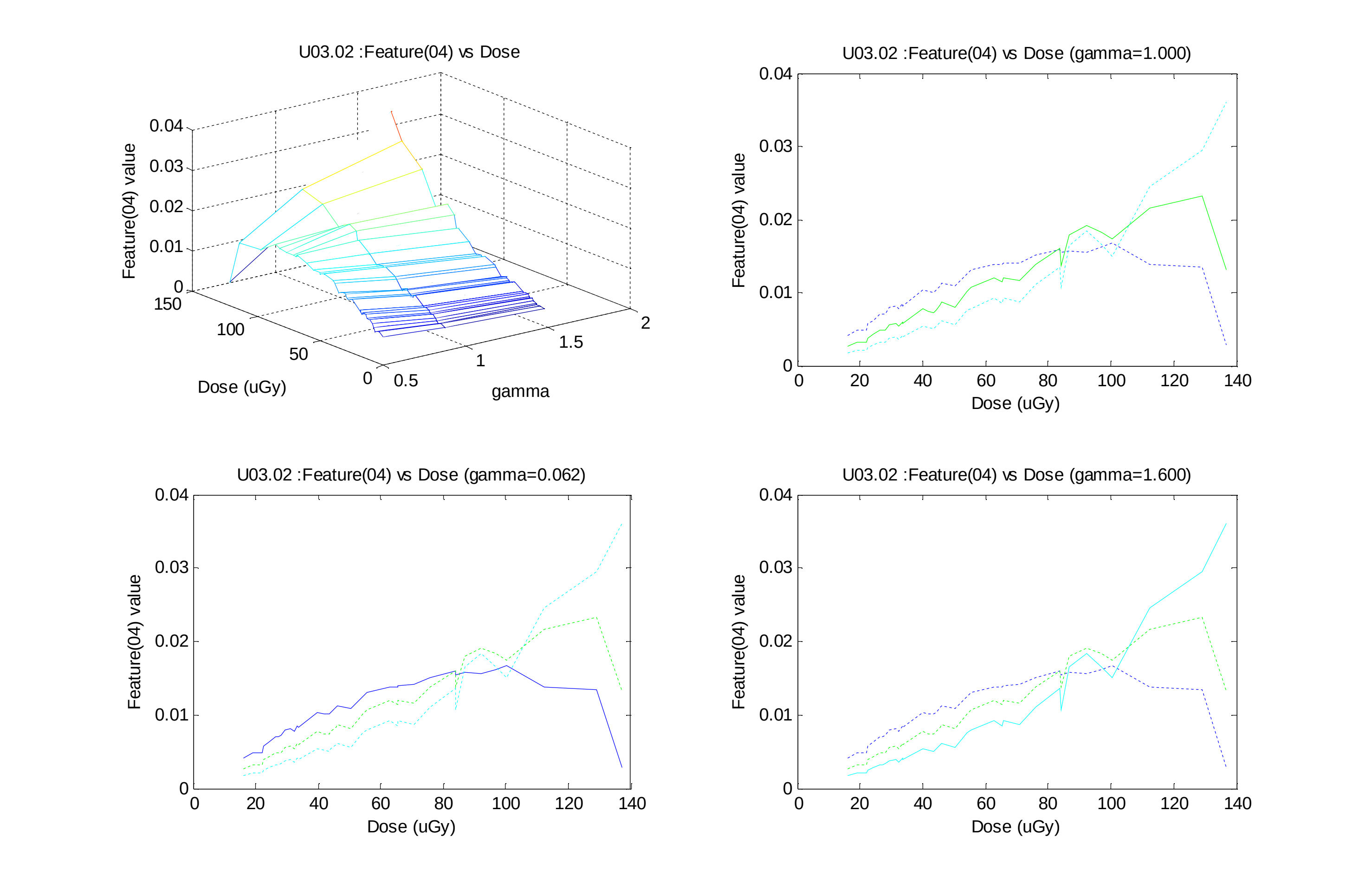
(3e) Example of GOOD feature function response (original set):



SF20: response curve is near-linear & consistent for all gamma levels

Issue # 3: Texture "signatures" against exposure rates

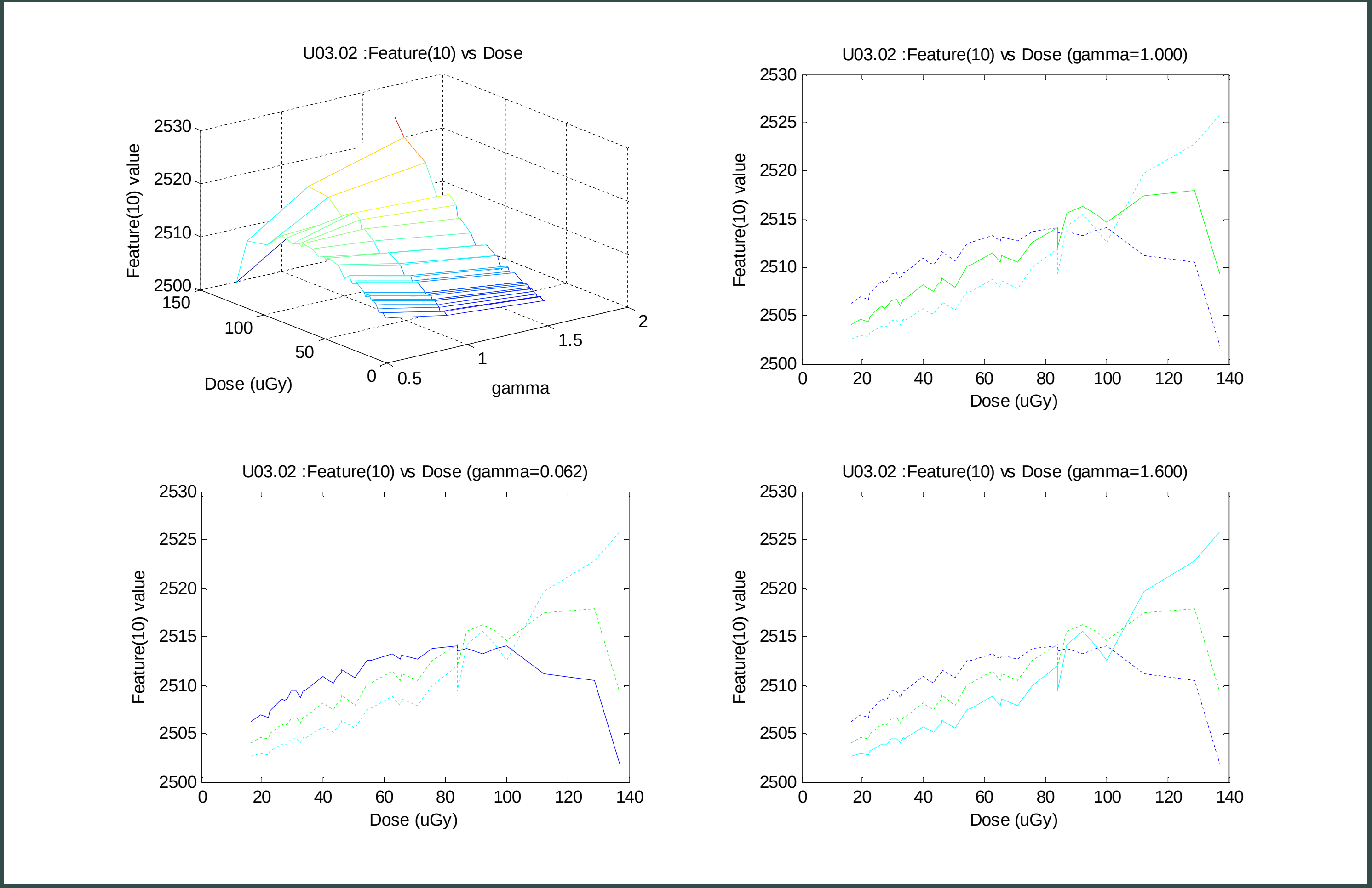
(3e) Example of possibly useful feature function response (revision):



STDEV: response curve is window-like for logarithmic histogram rescaling (g=0.62)

Issue # 3: Texture "signatures" against exposure rates

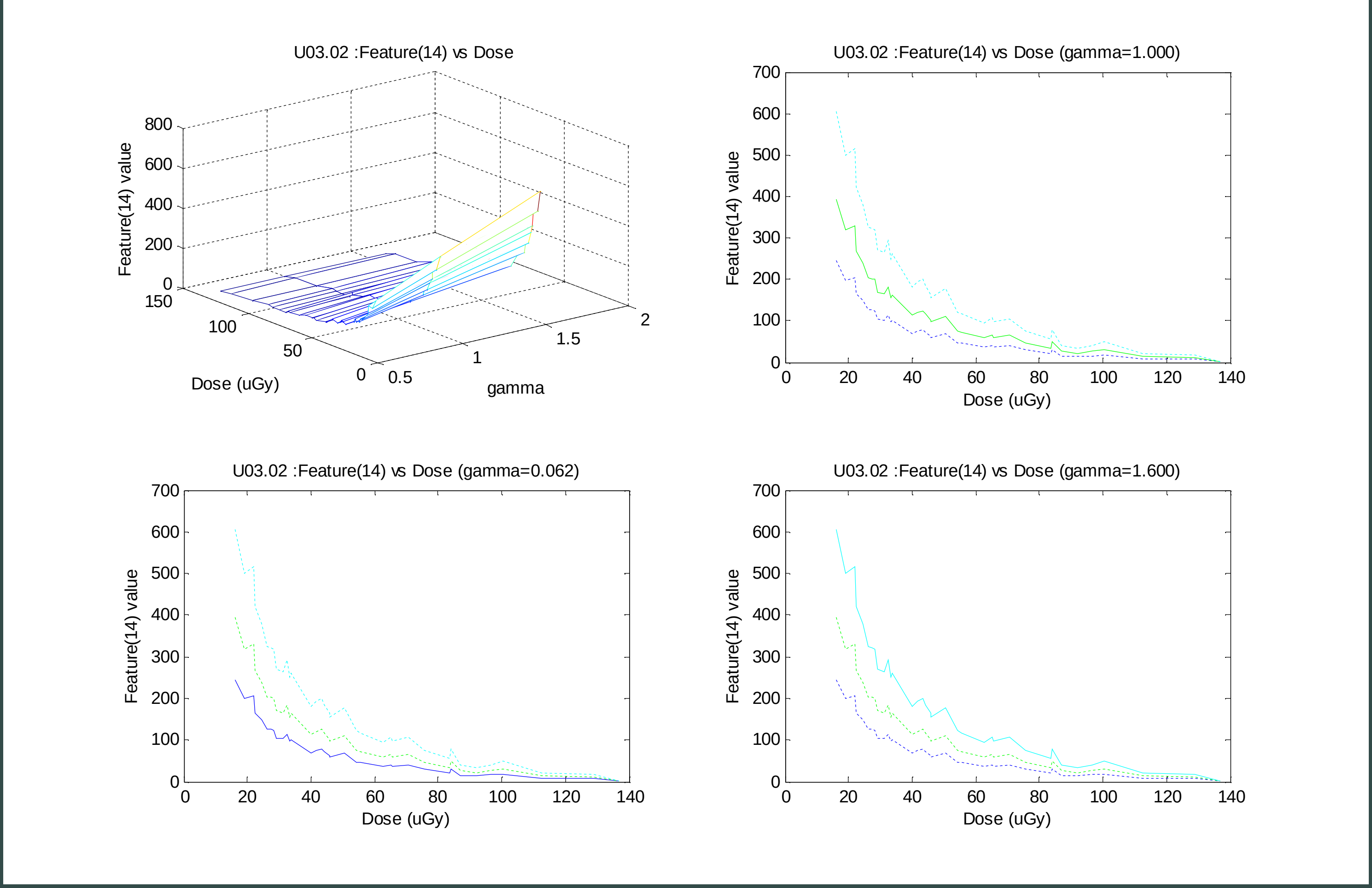
(3f) Example of possibly useful feature function response (new):



SURFACE, SF17: response is window-like for logarithmic histogram rescaling (g=0.62)

Issue # 3: Texture "signatures" against exposure rates

(3g) Example of possibly useful feature function response (new):



SF14: response is consistent (exp.decr) for all gamma levels

Issue # 3: Texture "signatures" against exposure rates

Results Summary

- Initial set of 7 textural feature extractors were verified as optimal.
- Additional feature functions (4) are possibly useful when using pre-processing.
- New response profiles refer to local processing only, not line-scanning sets.

Best feature functions (final):

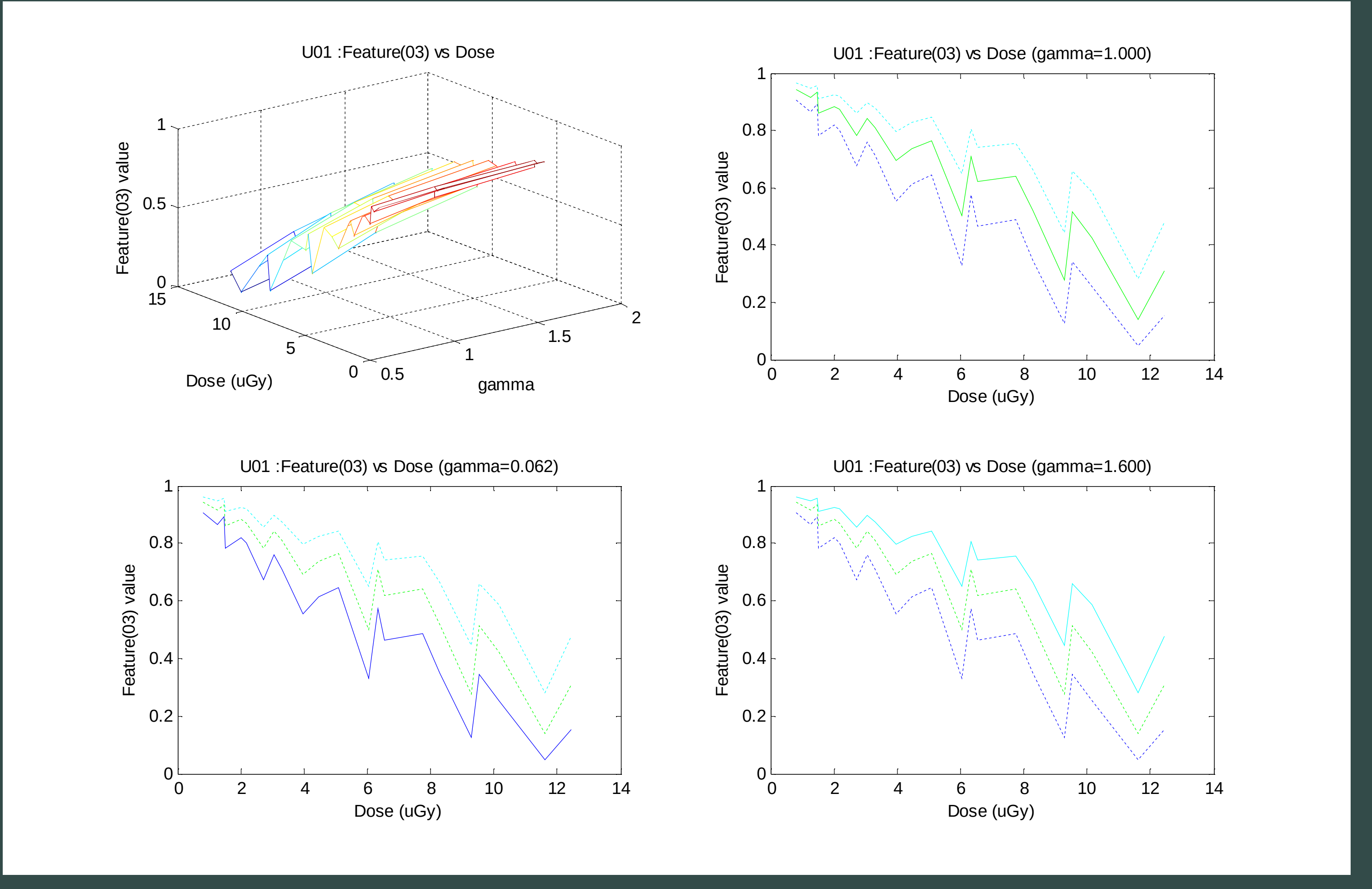
- F01: "MIN"
- F02: "MAX"
- F03: "MEAN"
- F07: "POWER"
- F11: "VOLUME"
- SF19: (normalized power)
- SF20: (normalized exposure)

Additional candidate feature functions:

- STDEV: $g < 1.00$
- SURFACE: $g < 1.00$
- SF17 (norm.surface): $g < 1.00$
- SF14 (mean.var): exp.decr. response

Issue # 4: Statistical effects of various image artifacts (DB3)

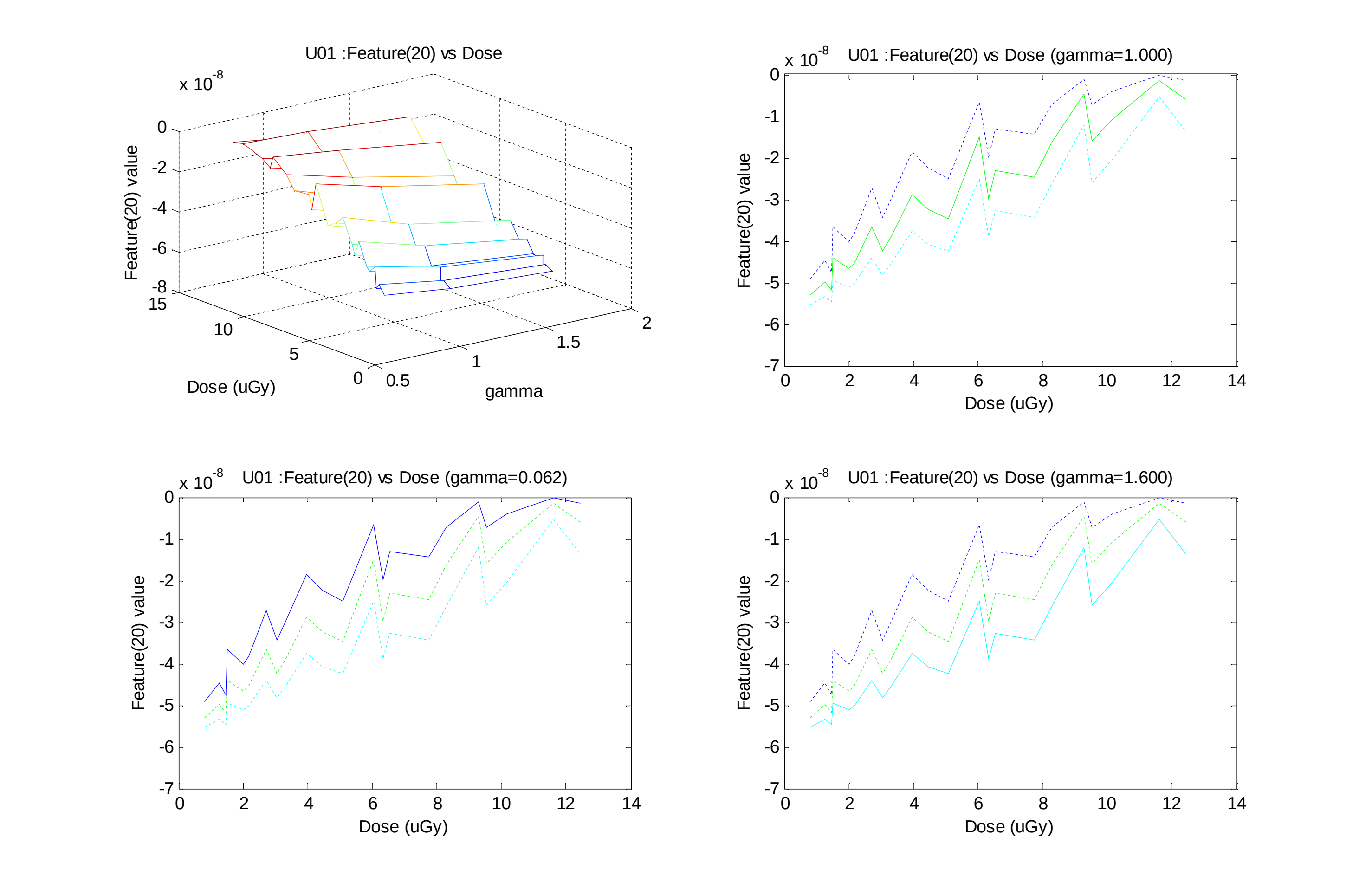
(4a) Example of MEAN feature function over malignant tumor tissue area (U01):



MIN, MAX, MEAN: response is similar but more “erratic” than on normal tissue areas

Issue # 4: Statistical effects of various image artifacts (DB3)

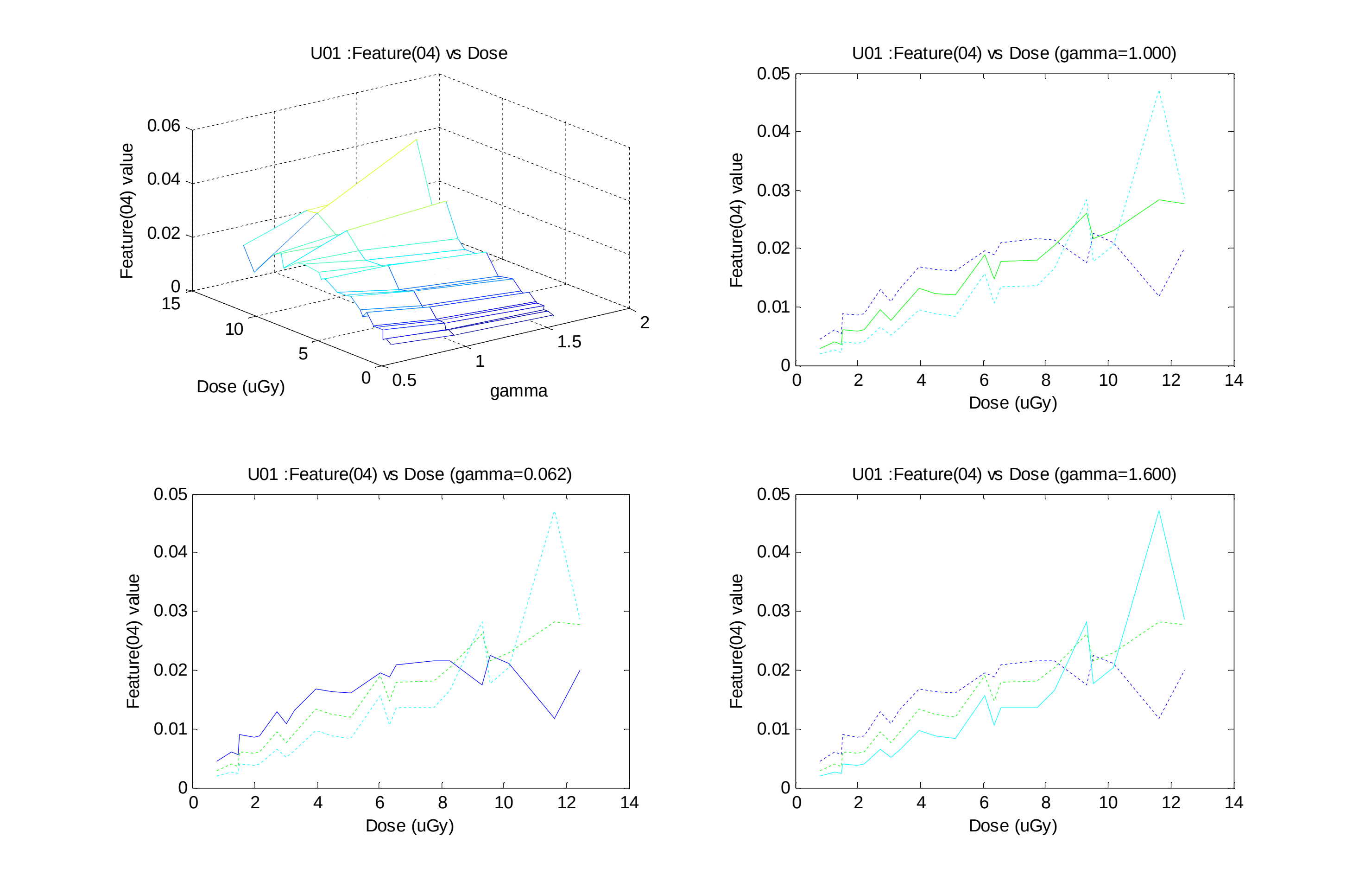
(4b) Example of SF20 feature function over malignant tumor tissue area (U01):



SF20: response is similar but more “erratic” than on normal tissue areas

Issue # 4: Statistical effects of various image artifacts (DB3)

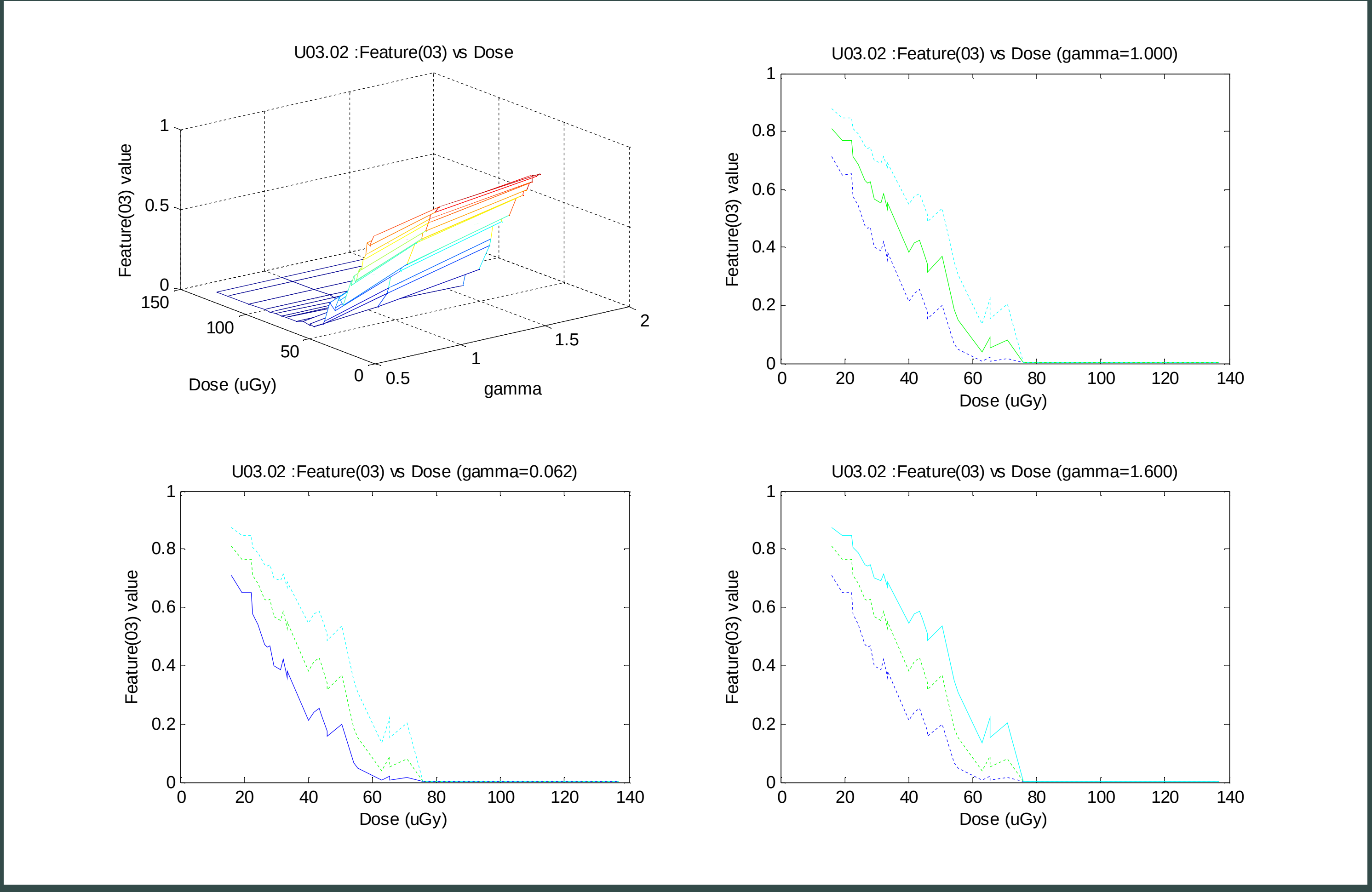
(4c) Example of STDEV feature function over malignant tumor tissue area (U01):



STDEV: response is similar but more "erratic" than on normal tissue areas

Issue # 4: Statistical effects of various image artifacts (DB3)

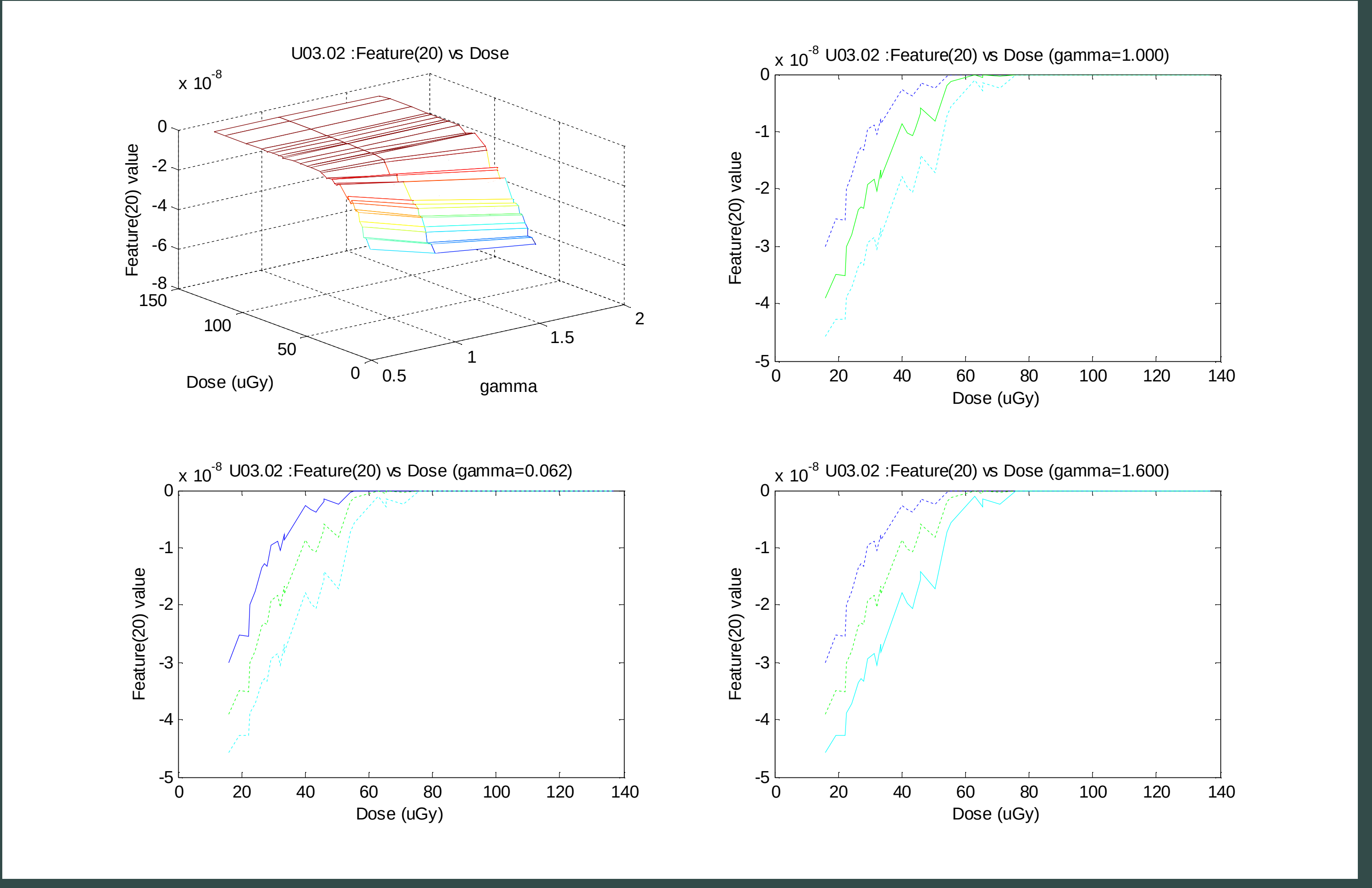
(4d) Example of MEAN feature function over background areas (U03.02):



MIN, MAX, MEAN: response curve drops more rapidly than on normal tissue

Issue # 4: Statistical effects of various image artifacts (DB3)

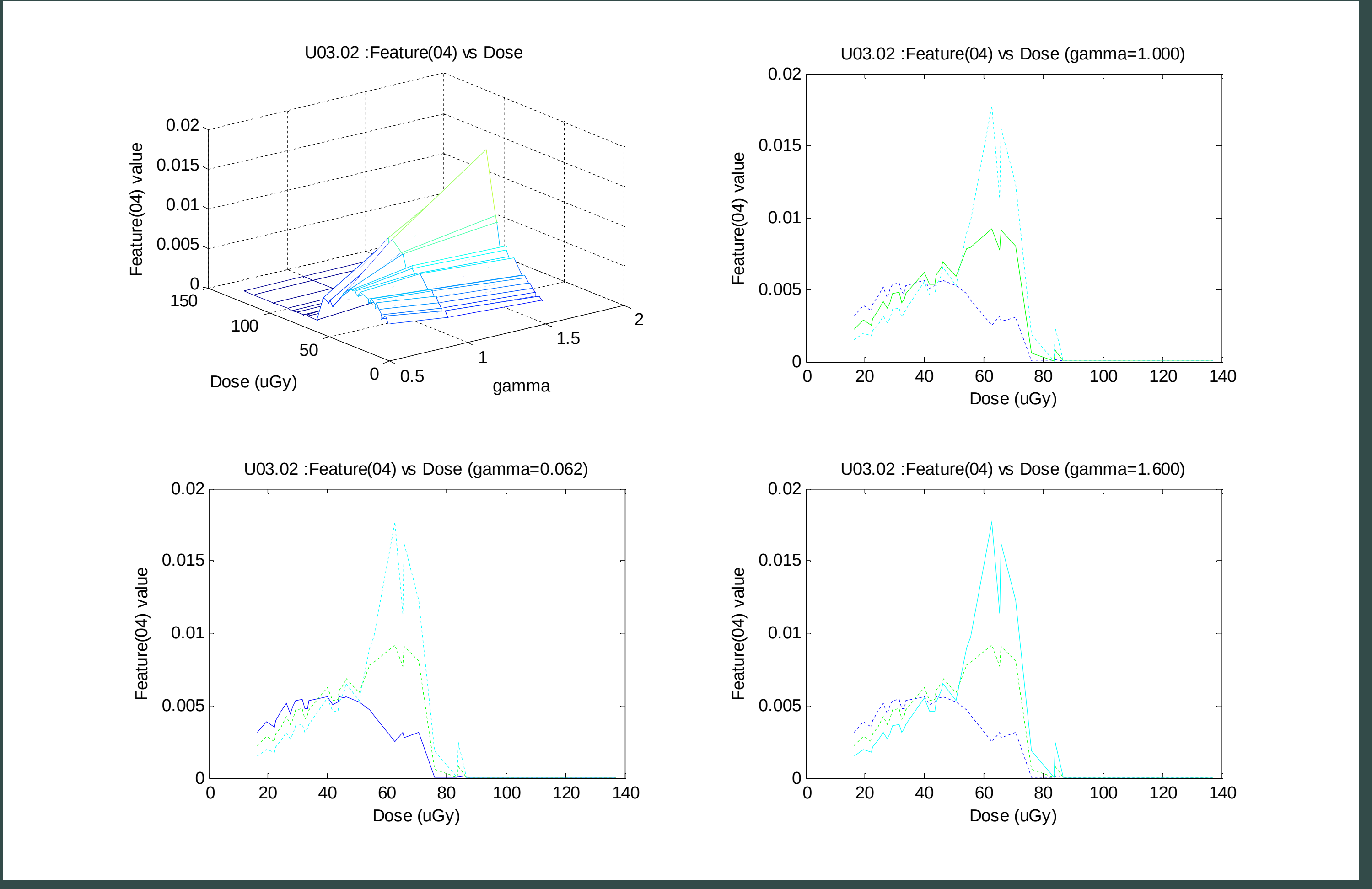
(4e) Example of SF20 feature function over background areas (U03.02):



SF20: response curve gets saturated more rapidly than on normal tissue

Issue # 4: Statistical effects of various image artifacts (DB3)

(4f) Example of STDEV feature function over background areas (U03.02):



STDEV: width of window-like profile is much narrower than on normal tissue

Issue # 4: Statistical effects of various image artifacts (DB3)

Results Summary: Malignant vs Normal tissue areas

- Comparative tests conducted on “U01” tissue sample (verified tumor presence)
- Both “optimal” (7) and “possibly useful” (4) feature functions were considered.
- Response profile is similar but more erratic on malignant tissue.
- Some evidence of primitive tissue discrimination capability in the selected sets.

Results Summary: Breast tissue vs background areas (artifacts)

- Comparative tests conducted on “U03.02” and “U04.03” tissue samples
- Both “optimal” (7) and “possibly useful” (4) feature functions were considered.
- Response profile is different on background areas, but with same properties.
- Differences in responses suggest limited effects of artifacts on tissue areas.

PredModel-2A/B: Textural Features Validation [23]

- ✓ Confirm SimModel-1A results over exposure and OD
- ✓ DB3: Global statistics, noise estimation, greyscale usage
- ✓ Efficiency and stability of textural feature extractors (20)
- ✓ Statistics: histogram pre-processing, image artifacts, etc.

D.8 report – Overview of final results: [23]

- Preliminary results from SimModel-1A were verified as significant
- Exposure rates and optical density models were verified as realistic
- Global statistics on DB3 suggest a valid operational profile.
- Preliminary selection of feature extractors were verified as adequate
- Effectiveness of selected features suggest some tissue-specialization
- Effects of DB3 image artifacts were verified as limited and non-relevant

Current Progress Overview:

- ✓ *D.8: overview of final conclusions*
- ➢ **D.9: sensor IC intelligence options & implementation**
- Further work & Proposals

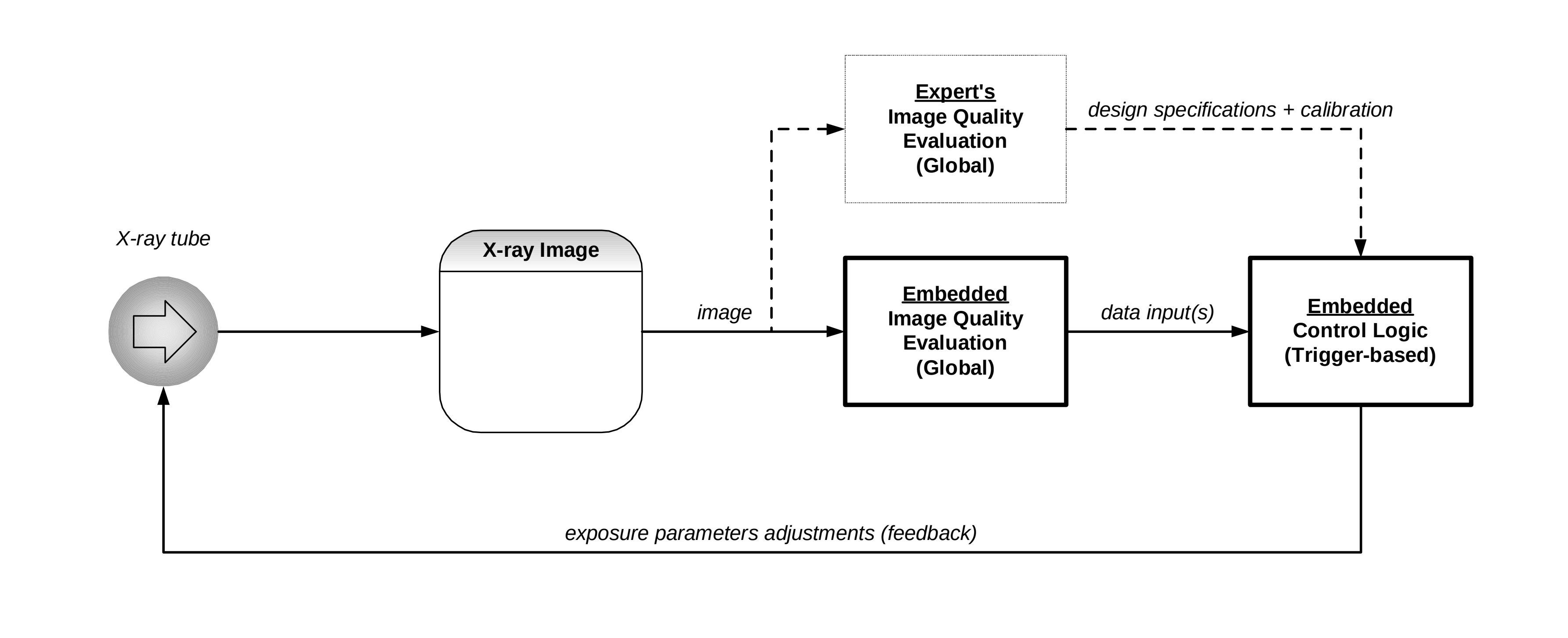
D.9 report – Overview of next deliverables:

- Exploitation of experts' response to image quality for optimal control
- Definition of optimal operational profiles for image processing modules
- Different approaches for providing "intelligence" to the sensor IC

"In-depth" analysis:

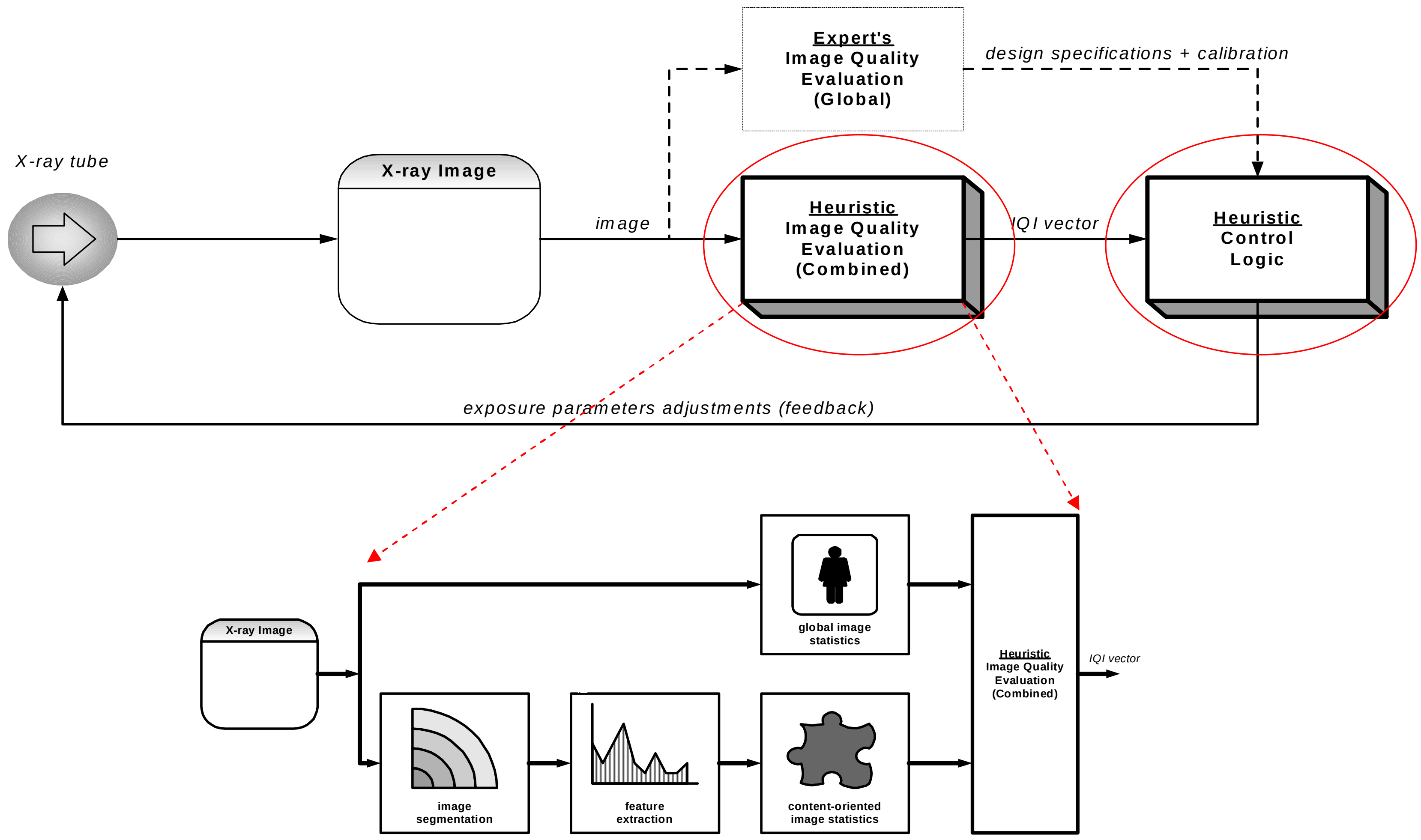
- OOP: Optimal Operational Profile (image processing)
- ORP: Optimal Response Profile (automatic IQ evaluation)
- OCP: Optimal Control Profile (feedback specifications)
- Implementation issues (options for input and control)

Current technology: Automatic Exposure Rate Control (AERC) [20]



- IQ evaluation: limited to OD saturation measurements
- Control module: trigger-based, provides timed cutoff of exposure
- "Open loop" – Human expert performs calibration to source
- "Off-line" – Human expert adjusts settings before the process starts

I-ImaS: "Intelligent" sensor, content-based decision on exposure adjustment [20]



State-transition model interpretation of "Heuristic Control Logic" module

$$\frac{\partial \overrightarrow{x(t)}}{\partial t} = f\left(\overrightarrow{x(t)}, \overrightarrow{u(t)}, t\right)$$

$$\overrightarrow{y(t)} = h\left(\overrightarrow{x(t)}, \overrightarrow{u(t)}, t\right)$$

t : current state (space / time)
u(t) : current input (settings)
x(t) : internal state (feature values)
y(t) : current output (image quality)

f (.) : state transition model (internal)
h (.) : transfer function (output)

- IQ evaluation: embedded into sensor IC, based on image texture analysis
- Control module: continuous feedback, provides adjustment of exposure settings
- "Closed loop" – System exploits the current output (resulting quality) as input
- "On-line" – System provides continuous self-adjustment during line-scanning

Options for state-transition model design

$$\frac{\partial \overrightarrow{x(t)}}{\partial t} = f\left(\overrightarrow{x(t)}, \overrightarrow{u(t)}, t\right)$$

$$\overrightarrow{y(t)} = h\left(\overrightarrow{x(t)}, \overrightarrow{u(t)}, t\right)$$

t : current box or scanning column
u(t) : current input set (**kVp**, **mAs**, image)
OR
current input set (**dose**, image)
x(t) : current state variables (feature values)
y(t) : current output (image quality index)

f (.) : state transition model (internal)
h (.) : transfer function (output)

- Transfer models *f(.)* and *h(.)* can be arbitrary functionals, linear or non-linear
- If both *f(.)* and *g(.)* are linear functions/mappings, control is linear
- If either *f(.)* or *g(.)* is non-linear, the control is non-linear (e.g. neural, fuzzy, etc).

Options for *f(.)* and *g(.)* design depends heavily on the complexity of the control logic (profile specifications) **AND** available processing time for the feedback.

If {mGy} is used instead of {kVp,mAs}, standard exposure profiles are necessary.

Case # 1: Linear options for both modules (Linear Control)

$$\frac{\partial \overrightarrow{x(t)}}{\partial t} = A \cdot \overrightarrow{x(t)} + B \cdot \overrightarrow{u(t)}$$

$$\overrightarrow{y(t)} = C \cdot \overrightarrow{x(t)} + D \cdot \overrightarrow{u(t)}$$

$$\overrightarrow{\hat{u}(t)} = \overrightarrow{u(t)} + K \cdot \overrightarrow{x(t)}$$

A , B : state transition coefficients
C , D : transfer function coefficients

when there is closed-loop feedback:
K : feedback coefficients for (new) input

In this case, the feedback can be used to provide stability and control over any type of (linear) control model.

- For stationary systems, all coefficients are constant over location and time
- Control system can be **designed** to be efficient and stable
- System can be easily implemented, using linear operations between matrices
- Besides the image itself, input can be either {mGy} OR {kVp,mAs}
- Output is always the (estimated) image quality, used to calculate “adaptation”

Case # 2: Non-linear options for one or both modules (Non-linear Control)

$$\frac{\partial \overrightarrow{x(t)}}{\partial t} = f\left(\overrightarrow{x(t)}, \overrightarrow{u(t)}, t\right)$$
$$\overrightarrow{y(t)} = h\left(\overrightarrow{x(t)}, \overrightarrow{u(t)}, t\right)$$

f (.) : state transition model (internal), essentially the gradient of any any type of mapping between the input {kVp/mAs OR mGy} and the resulting features space.

h (.) : transfer function (output), which is the actual mapping of feature vectors to the image quality index.

- The input u(t) here includes ALL input, i.e. exposure settings, image, feedback.
- Control system is too complex to be analytically designed as efficient and stable.
- System modules have to be trained according to suggestive input-output sets.
- System usually includes non-linear processing structures for calculating output.
- Besides the image itself, input can be either {mGy} OR {kVp,mAs}
- Output is always the (estimated) image quality, used to calculate “adaptation”

Adaptation Strategies – Preliminary assessment

(1) “Simplistic” : No consideration for calculating gradients of feature vectors, use only current input {kVp/mAs OR mGy} and current state variables (feature values) to decide on the exact feedback.

(2) “Fully adaptive” : Assume nothing, use at least 2-3 consecutive measurements to provide local gradient vector and calculate feedback, on the basis of required adjustment for maximal quality index (vector) increase.

(3) “Model matching” : Assume prior knowledge of the general morphology of the image quality space, use only current measurement, rescale the general model into the (estimated) current data, estimate current gradient vector from the rescaled model, and adjust current quality index (vector) using local stepping OR large “leap” towards optimum.

Note: Details are to be concluded in the D.9 report (Feb.2005)

Adaptation Strategies – Practical considerations and limitations

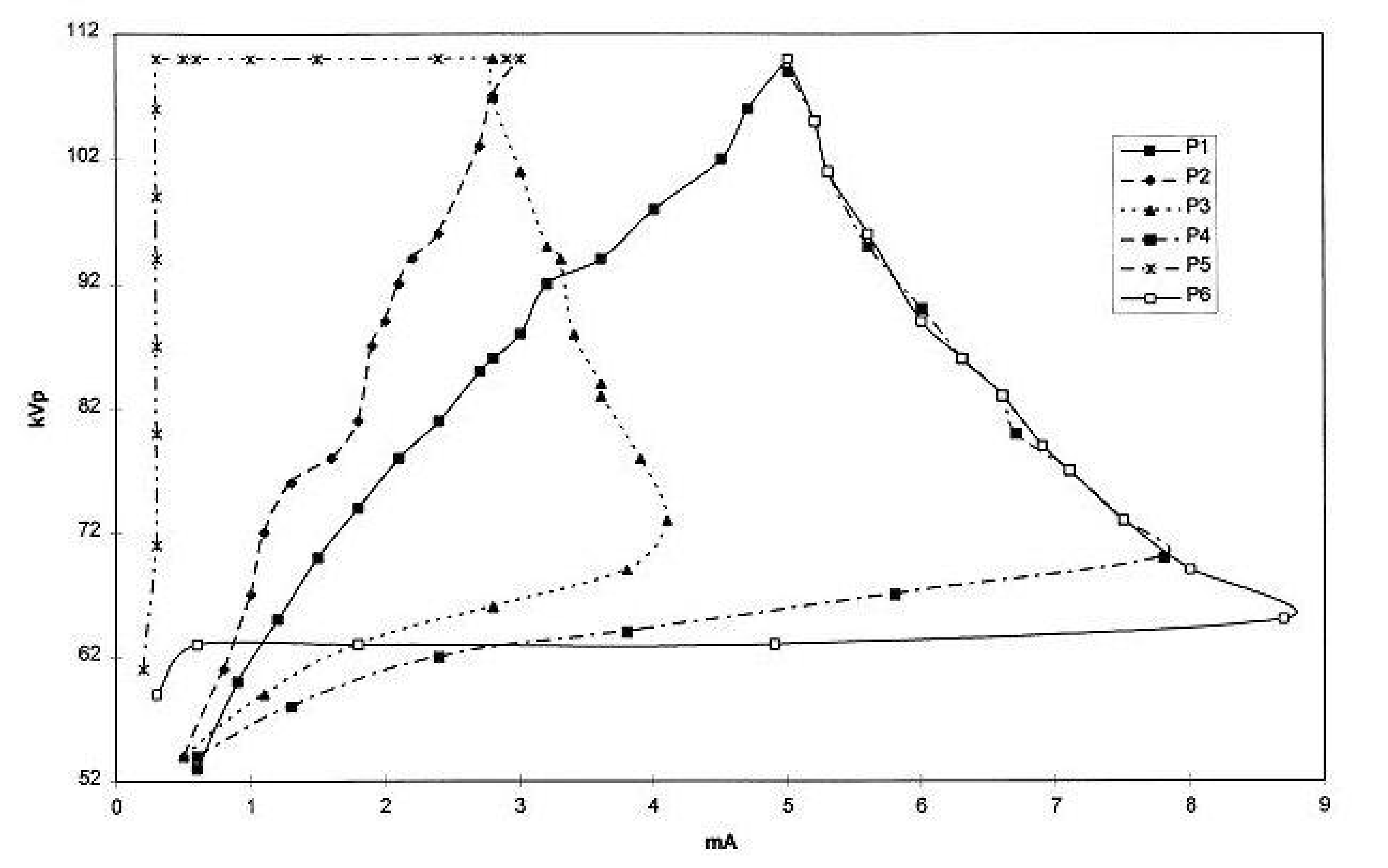
►"Simplistic" : Easy to implement, provided a straight-forward "behavioral" design is evident for mapping feature vectors (states) into regions of optimal or near-optimal image quality (output). Feedback is calculated by means of reverse-mapping between image quality index and input.

►"Fully adaptive" : Does NOT depend on any type of embedded "prior knowledge" from experts and adaptation is local (iterative). However, it needs a minimum of 2 (for mGy input) or 3 (for kVp/mAs input) consecutive measurements at different states. Feedback is calculated directly.

►"Model matching" : Prior "template" map is used as guideline for the image quality index space embodying the experts' knowledge (response). This map is rescaled against current state (feature vector) and estimated value of image quality index. Feedback is calculated directly for either local or global optimization.

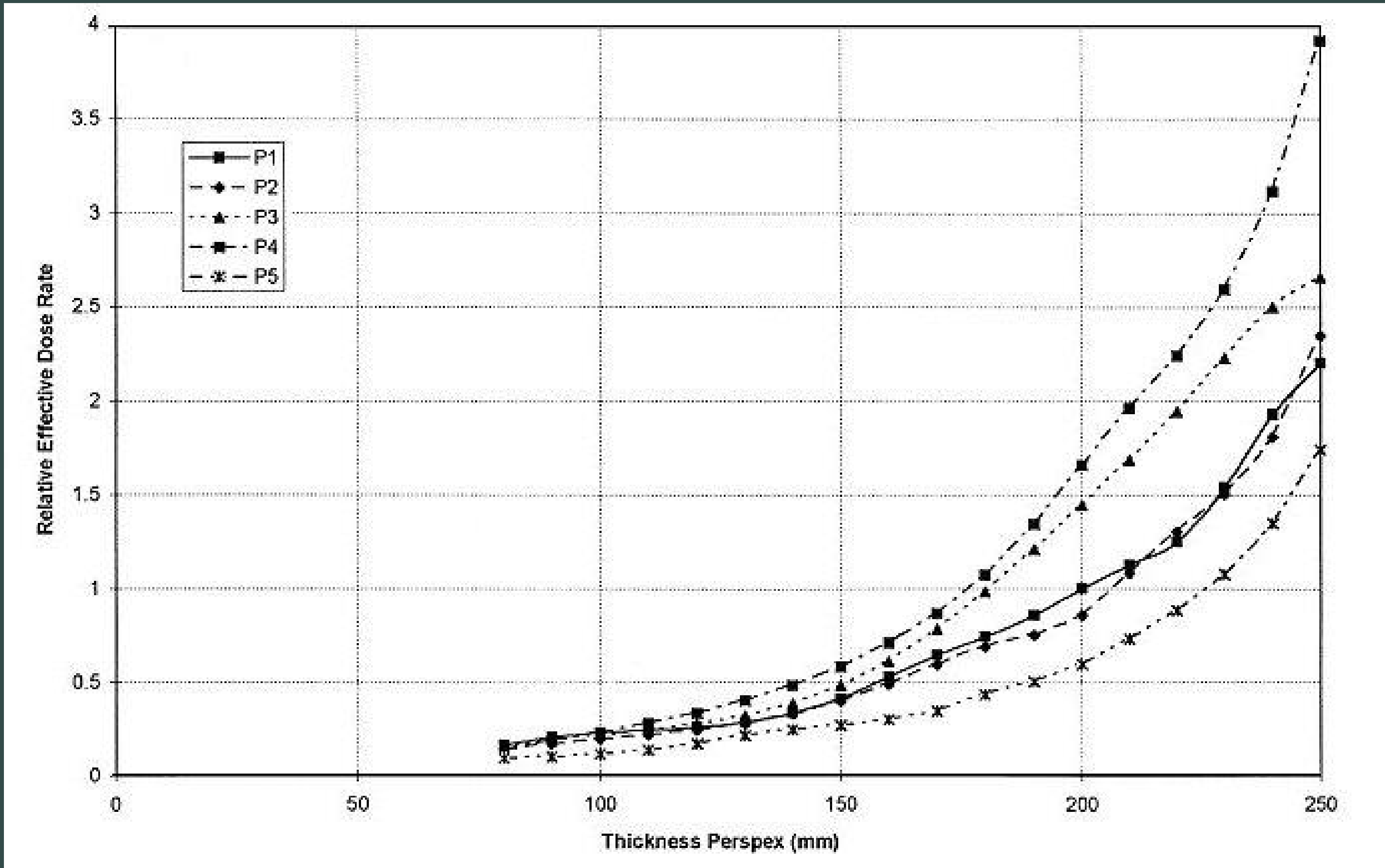
Note: Details are to be concluded in the D.9 report (Feb.2005)

Exposure profiles: Standard AERC curves (fluoroscopic)



Standard kVp/mAs exposure profiles (AERC) for a modern fluoroscopic unit [11].
P1: std 5 mA, P2: std 3 mA, P3: 4 mA high contrast, P4: 8 mA high contrast, P5: "paediatric", P6: "iodine"

Exposure profiles: Patient dose vs thickness (stomach)



Relative patient effective dose for a stomach examination at various standard exposure profiles on a conventional X-ray machine [11].

Current Progress Overview:

- ✓ *D.8: overview of final conclusions*
- ✓ *D.9: sensor IC intelligence options & implementation*
- ➢ **Further work & Proposals**

Further Progress Requirements (WP3):

1. **Combine, formalize and organize image quality evaluations provided by expert radiologists (Trieste, Athens)**

2. **Investigate experts' evaluations (overall) against the selected feature functions and create typical image quality maps ("templates").**

3. **Decide on the type and the specifications of the sensor IC intelligence, affordable by the current hardware design and resources.**

4. **Provide typical OOP (operational), ORP (response) and OCP (control) profiles for the system's "intelligence", according to the specificity and extend of the sensor IC specifications available now, as well as possible future enhancements.**

Note: Details on issues 1-3 are to be concluded in the D.9 report (Feb.2005), while issue 4 will be suggestive for future applications and implementations.

Current Progress Overview:

- ✓ *D.8: overview of final conclusions*
- ✓ *D.9: sensor IC intelligence options & implementation*
- ✓ *Further work & Proposals*

Suggestive References:

[11] *C.J.Martin, D.G.Sutton, P.F.Sharp*, "Balancing patient dose and image quality", *Applied Radiation and Isotopes*, 50 (1999) pp.1-19.

[20] *S.Theodoridis, D.Cavouras, H.Georgiou,* "I-ImaS: Preliminary Analysis Report and Proposed Design", *Dept. of Informatics & Telecomm., Univ. of Athens, Greece,* Mar.2004.

[21] *I-ImaS, Workpackage 3*, "Update on current progress and preliminary results for the on-chip processing", *presentation for 2nd I-ImaS meeting, Amsterdam, 26-27 May*, 2004.

[23] *I-ImaS, Workpackage 3 – Deliverable D.8*, "Translating information signatures to a sequence of well-defined processing functions", Dec.2004.

[24] *I-ImaS, Workpackage 3*, "Update on current progress and report for deliverable D.8", presentation for 3rd I-ImaS meeting, London, 12-13 October, 2004.