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A Bayesian Image-Domain Approach to Virtual Non-Contrast Imaging in Dual-Energy HyperSight CBCT

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ABSTRACT

Purpose: To develop and evaluate a Bayesian image-domain virtual non-contrast (VNC) reconstruction method for HyperSight dual-energy cone-beam CT (DE-CBCT), enabling iodine suppression while preserving underlying anatomical Hounsfield unit values.

Methods: A calibration was established using a series of multi-energy phantom measurements to characterize the attenuation properties of water, iodine, fat, lung, and soft-tissue-equivalent materials. The proposed method uses low- and high-energy CBCT images and incorporates uncertainty-aware regularization to improve robustness against noise and spectral overlap. VNC images were generated by estimating and removing the iodine component while retaining non-enhancing anatomy. Performance was evaluated using an electron density phantom containing inserts with iodine concentrations ranging from 14.6 to 64.1 mg/mL.

Results: The proposed approach successfully removed iodine enhancement across all tested concentrations while preserving the appearance of the underlying anatomy. The Bayesian credible interval provided voxel-wise uncertainty estimates, offering insight into the confidence of the material decomposition and VNC reconstruction. The estimated iodine maps accurately recovered iodine concentrations over a wide range of concentrations. Greater deviation was observed for the 14.6 mg/mL vial, likely due to the insert's proximity to the iodine–bone separability threshold.

Conclusion: A Bayesian image-domain VNC framework for HyperSight DE-CBCT was developed and evaluated in phantom studies, demonstrating promising performance. The method enables accurate iodine suppression, quantitative iodine mapping, and voxel-wise uncertainty estimation. This framework may support more streamlined CBCT-based adaptive radiotherapy workflows.

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INTRODUCTION

Recent advances in cone-beam CT (CBCT), such as the HyperSight system (Varian Medical Systems, CA), have substantially improved image quality and Hounsfield Unit (HU) accuracy [1], enabling quantitative imaging applications beyond patient positioning. Dual-energy CBCT (DE-CBCT) enables virtual non-contrast (VNC) imaging from a single contrast-enhanced acquisition, reducing additional imaging requirements and potentially facilitating CT simulation-free (direct-to-unit) and adaptive radiotherapy workflows [2]. In this work, we developed a Bayesian image-domain VNC reconstruction method for HyperSight DE-CBCT, designed to achieve robust iodine suppression while preserving the underlying anatomical structures.

METHODS

The method combines material-specific classification with voxel-wise selective Bayesian inference to estimate the native tissue attenuation and iodine concentration from paired 80 kVp and 140 kVp measurements to generate a 125 kVp VNC image.
The workflow (Fig.1) consists of four stages:

i. **Image-domain Mahalanobis Distance Parametric ClassificaTion (IMPACT)**
ii. **Probabilistic voxel classification**
iii. **Bayesian inference with a conservation-of-volume model and a Markov Chain Monte Carlo (MCMC) solver**
iv. **Volex energy mapping and output generation**

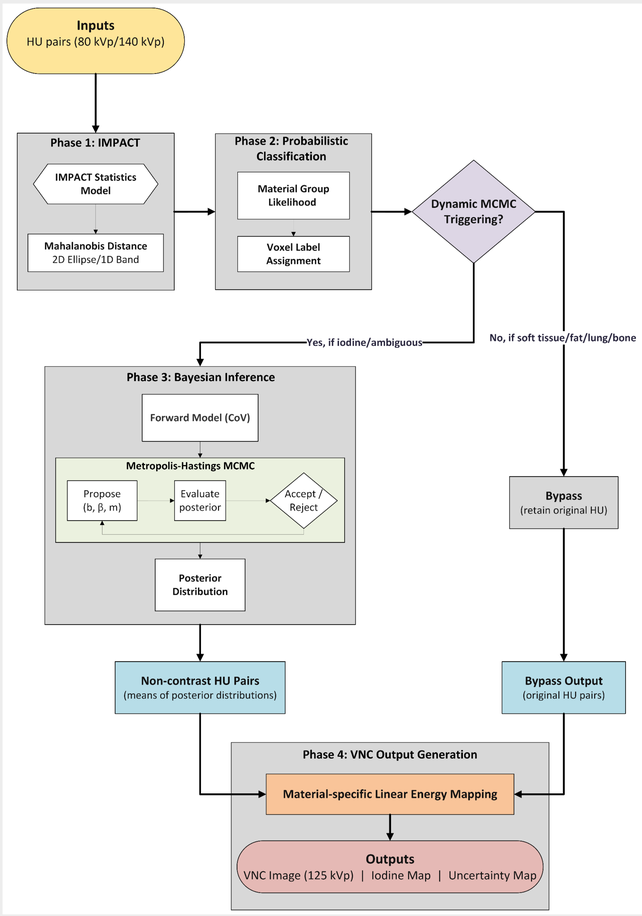

Figure 1. Flow chart of the proposed VNC algorithm

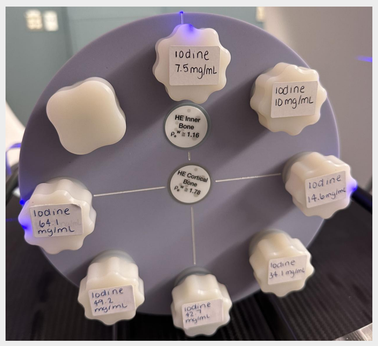

Figure 2. Advanced Electron Density (AED) phantom (Sun Nuclear, FL) with inserts

RESULTS

Phase 1: IMPACT (Fig.3)

A previously developed IMPACT classification model [3] was used to characterize material groups in dual-energy HU space.

- Soft tissue and fat were represented using 2D Mahalanobis distance for bivariate Gaussian distributions:
$$D^2 = (y-\mu)^T \Sigma^{-1} (y-\mu)$$
- Bone, lung, and iodine exhibit approximately linear trajectories in dual-energy space and were modeled using 1D Mahalanobis distance:
$$D_\perp^2 = \frac{({v_2}^T(y-\mu))^2}{\lambda_2}$$

where $y = [y_L, y_H]^T$ denotes the HU acquired at 80 kVp and 140 kVp; μ is the mean HU of the calibration material group; V_2 is the eigenvector in minor axis and λ_2 is the associated eigenvalue.

To learn more about IMPACT, please join ***TU-510-220 - Development of a Dual-Energy Cone Beam CT Technology on Ethos Hypersight****, B. Smith & M. Sattarivand, at 5:38 PM on Tuesday, July 21, in Room 220.*

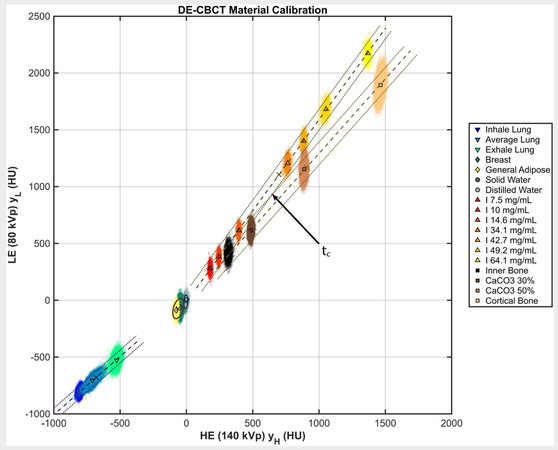

Figure 3. 2D HU map of voxels from five calibration material group

Phase 2: Probabilistic Classification (Fig.4)

- The likelihood of a voxel belonging to a material group g can be defined as:
$$\tilde{P}_g(y) = \begin{cases} \exp(-\frac{1}{2}D^2), & 2D\ ellipse \\ \exp(-\frac{1}{2}D_\perp^2), & 1D\ band \end{cases}$$
- A normalized probability vector represents the relative confidence that the voxel belongs to each calibrated material:
$$P_g(y) = \frac{\tilde{P}_g(y)}{\sum_{g'} \tilde{P}_{g'}(y)}$$
- Voxel label assignment is generated as:
$$\hat{g} = \arg\max P_g(y)$$
- Voxels with projected iodine concentrations or bone densities below t_c criterion were designated as ambiguous.
- Iodine-enhanced ambiguous voxels go through the Bayesian inference. Bone/soft tissue/fat/lung voxels bypass the computationally heavy Bayesian inference.

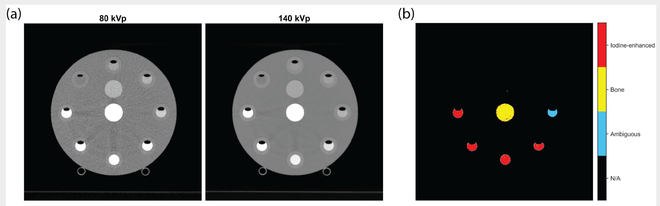

Figure 4. (a) Representative 80 kVp and 140 kVp CBCT image slices; (b) Voxel label assignments produced by the proposed framework Phase 2

Phase 3: Bayesian Inference

- For each voxel, the unknown state is described as:
$$\theta = (b, \beta, m)$$
where $b = [v_L, v_H]^T$ is the base material HU vector, β is the iodine volume fraction, and m is a discrete latent variable for material mode switching.

- The predicted dual-energy HU vector is modelled with the assumption of conservation-of-volume (CoV) as:
$$y_{pred}(\theta) = (1-\beta)b + \beta u_C$$
- The conditional joint posterior probability of θ can be written as:
$$p(\theta \mid y) \propto \mathcal{L}(y|\theta) \cdot \pi(\theta)$$
- Assuming multivariate Gaussian distribution for HU with image noise, the likelihood function in log-form can be written as:
$$\log \mathcal{L}(y|\theta) \propto -\frac{1}{2}\left(y - y_{pred}(\theta)\right)^T \Sigma_{noise}^{-1}(y - y_{pred}(\theta))$$
- The prior $\pi(\theta)$ can be expressed as:
$$\pi(\theta) = p(b \mid m)p(m)p(\beta)$$
  - For soft-tissue mode ($m = 0$) or bone mode ($m = 1$), $p(b \mid m)$ in log-form:
$$\log p(b \mid m) \propto \begin{cases} -\frac{1}{2}(b-\mu_S)\Sigma_S^{-1}(b-\mu_S)^T, & m = 0 \\ -\frac{1}{2}(b-\mu_B)\Sigma_B^{-1}(b-\mu_B)^T, & m = 1 \end{cases}$$
  - The mode prior $p(m)$ is guided by the probabilistic classification results P_g from Phase 2 for a given voxel:
$$p(m) \propto \begin{cases} P_{soft\ tissue} + P_{fat} + P_{lung} + P_{iodine}, & m = 0 \\ P_{bone}, & m = 1 \end{cases}$$
  - The iodine fraction prior $p(\beta)$ serve as a L_1-type sparse regularization:
$$p(\beta) \propto e^{-\kappa\beta}$$
- Posterior base material means $[\hat{v}_L, \hat{v}_H]$ were obtained using Metropolis–Hastings MCMC.

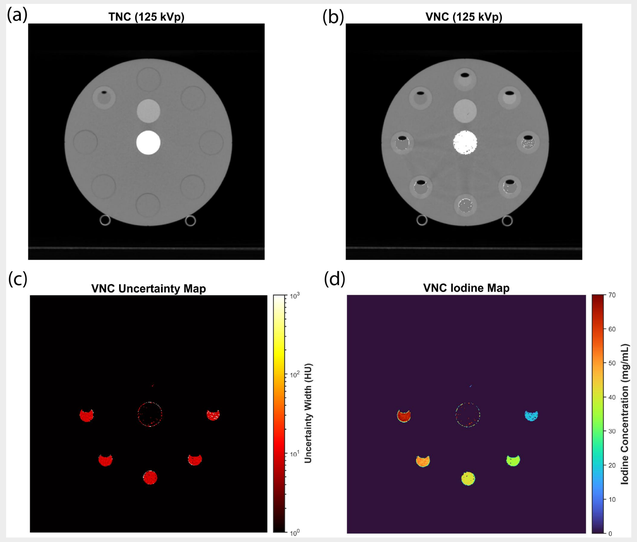

Figure 5. (a) Reference TNC image acquired at 125 kVp; (b) Synthetic 125 kVp VNC image; (c) Corresponding voxel-wise uncertainty map with a log-scale colormap; (d) Reconstructed iodine concentration map (mg iodine/mL)

Phase 4: Output Generation (Fig.5)

- The final VNC attenuation is synthesized from the original low-kVp (y_L) and high-kVp (y_H) spectral measurements using a weighting factor ω :
$$VNC = \omega y_L + [1-\omega]y_H$$
- The quantitative iodine concentration is computed by multiplying the average iodine fraction $\hat{\beta}$ with the iodine concentration of the contrast agent I_0
$$\hat{I} = I_0\hat{\beta}$$

CONCLUSIONS

A Bayesian image-domain VNC method for HyperSight DE-CBCT was developed and demonstrated promising performance in phantom studies, with potential to support direct-to-unit adaptive radiotherapy.

REFERENCES

1. Yashayaeva A, MacDonald RL, Robar J, Cherpak A. Evaluation of a Metal Artifact Reduction Algorithm for Image Reconstruction on a Novel CBCT Platform. J Appl Clin Med Phys. 2024;25(11):e14516.
2. Malkov VN, Kemp BJ, Ferrero A, Buchholtz L, Park SS, Kavanaugh JA. Adaptive-driven CT simulation-free multi-fraction SBRT radiotherapy: Initial clinical experience. J Appl Clin Med Phys. 2025;26(8):e70147.
3. Smith B, Sattarivand M. Development of a dual-energy cone beam CT technology on Ethos HyperSight. Presented at: AAPM Annual Meeting; 2026.