Anomaly Detection in X-ray Backscatter Leg Images Using Training Data

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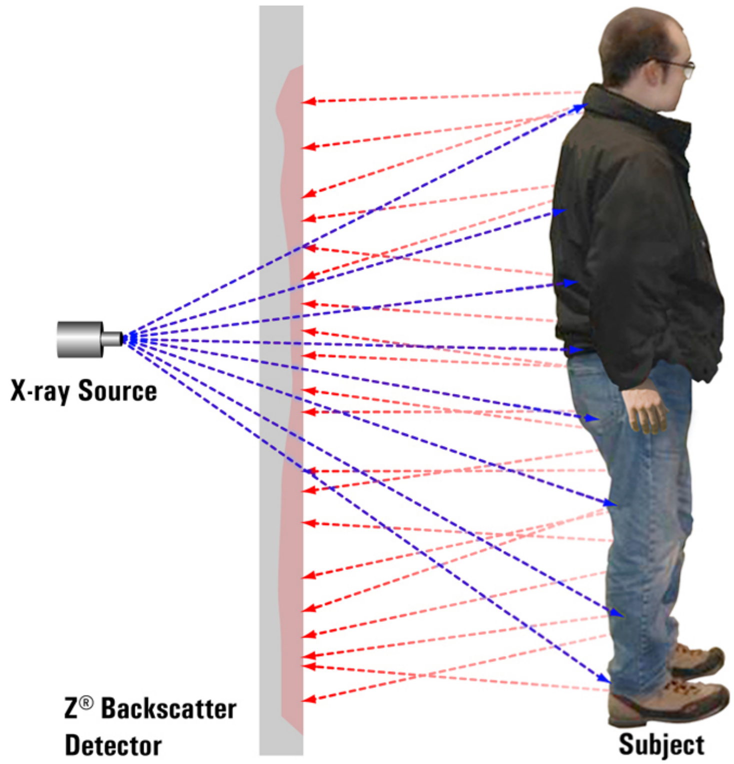
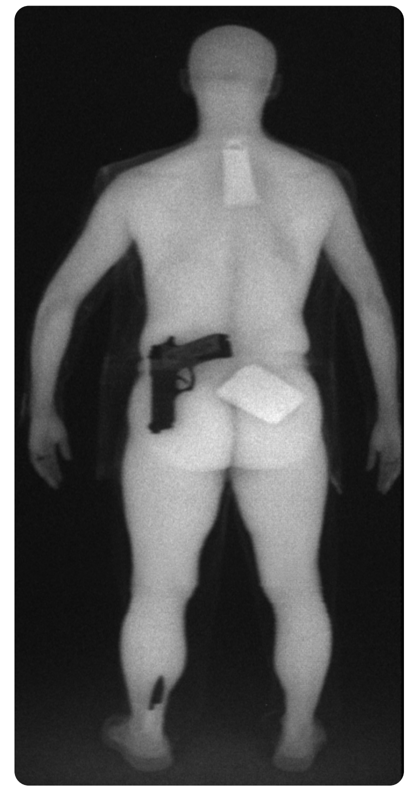
Backscatter X-ray Technology

- Backscatter X-ray technology collects data by reflecting an X-ray beam from a target to a detector on the near side.
- The reflected intensity is dependent on:
  - Atomic Number (Z)
  - Density
- Backscatter tends to favor low-Z, high density materials





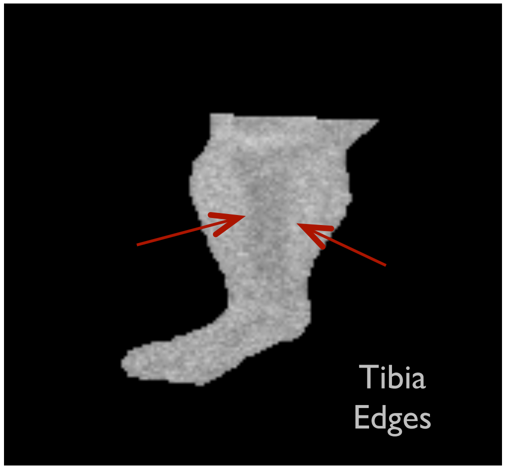
AS&E SmartCheck HT Personnel Screening System

- Uses X-ray backscatter technology to detect anomalies
- Displays images to operator, with anomalies marked for inspection
- Two-Sided System
  - Front Image
  - Back Image
  - Transmission Image

SmartCheck HT System

Problem Description

- Anomaly Detection
  - Full-body scan is processed and displayed to operator
  - Anomalous regions are marked for further screening
- Edge Information is Critical
  - Metals are denser than organics
  - Organic anomalies add discontinuities to body surface
- Problem for Leg Images
  - Geometry of scanner produces lower signal-to-noise ratio in leg region
  - Tibia edges cause high false-alarm rate
    - Higher density
    - Close to surface of leg



Anomaly-Detection Algorithm

- Focus on front-side lower leg region
  - Well-defined set of issues making this a problem where we could show progress over summer-length period
  - Methods adaptable to more challenging parts of the body
- Use training data to determine edge distribution

1. Segment leg region of images
2. De-noise leg images while preserving edges
3. Map leg images into common coordinate system
4. Detect anomalies using training image statistics

Segmentation and Cropping

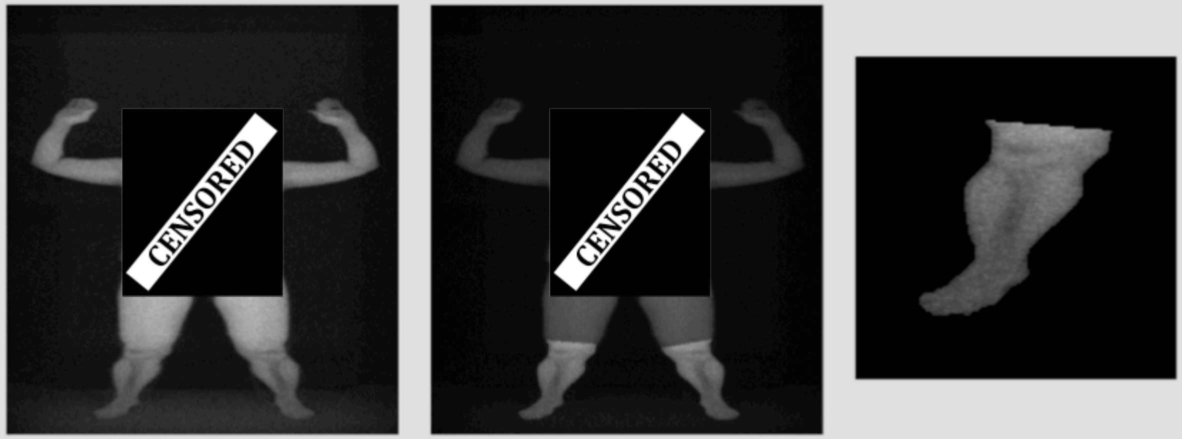
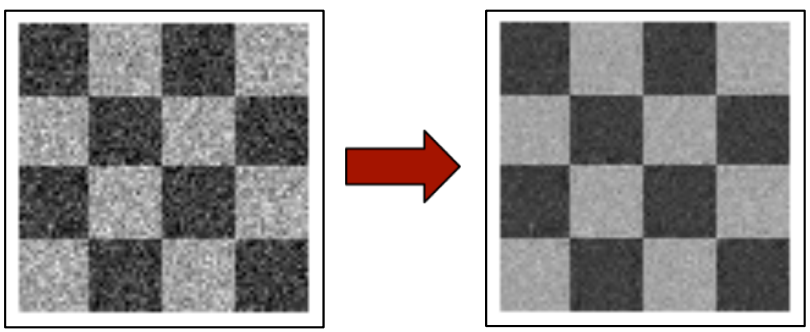


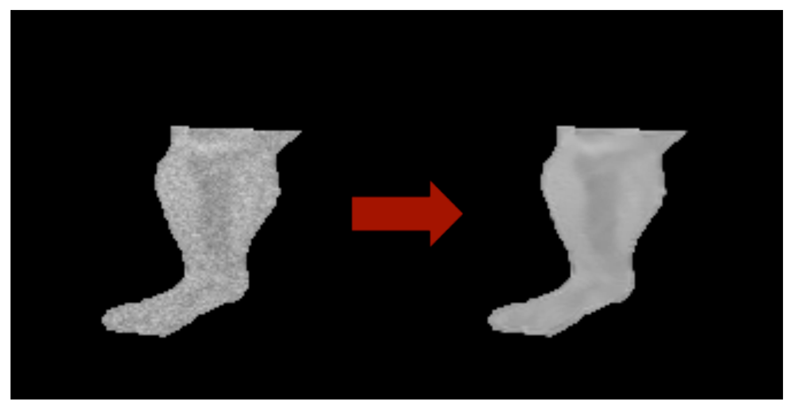
Figure 1. (Left) SmartCheckHT full-body X-ray backscatter image. (Censored for privacy.)
(Middle) Full-body image with segmentation mask and manual crop highlighted.
(Right) Leg image after background subtraction and manual crop.

- SmartCheckHT test images from American Science and Engineering
- Used AS&E segmentation masks for background subtraction
- Manually cropped leg-region for each leg

De-noising Filter with Edge Preservation

- Images dominated by Poisson noise
  - Need to remove noise while preserving edges
- Non-local means filter
  - Estimates the value at pixel **x** by taking the average of all pixels whose neighborhood "looks like" the neighborhood around **x**.
  - Makes use of repeated details in image
  - Removes noise while preserving edge structures (much less blurring than, for example, Gaussian filtering)

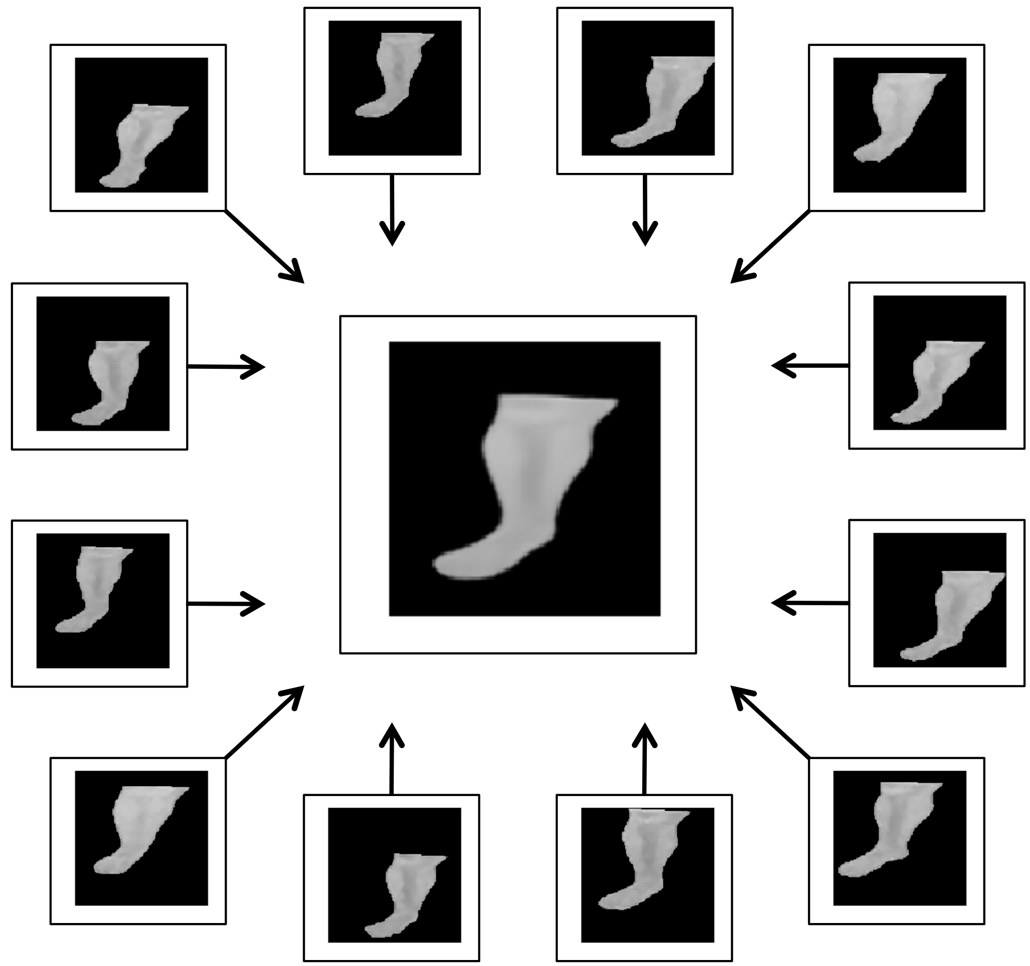




Alignment and Registration

- Transform leg images into common coordinate system for valid statistical analysis computation.

1. Affine Transformation
   - Minimizes differences in position, scale, orientation, and skew.
2. Non-Rigid Registration
   - Deals with differences in subject posture (e.g. knee angle, ankle shape).

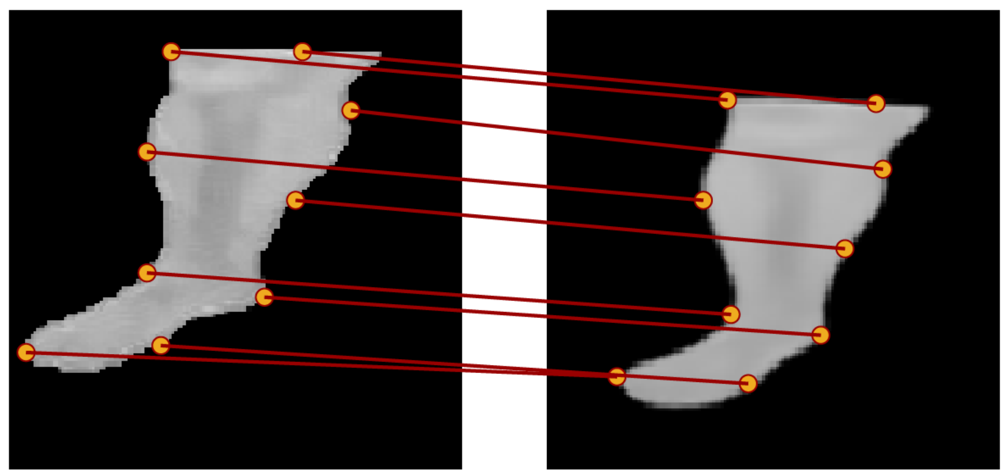


Affine Transformation

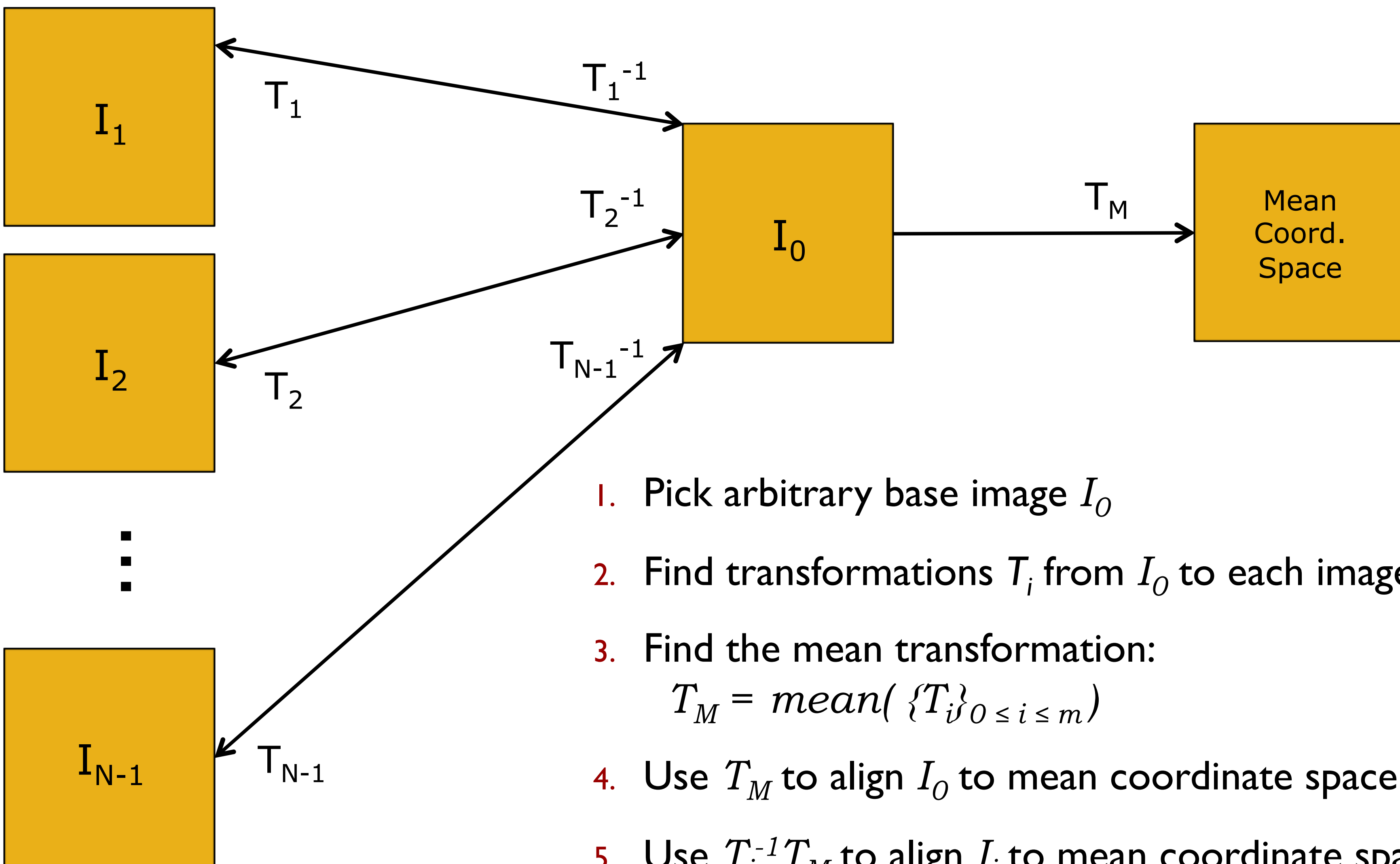
- Select m boundary reference points for each image.
- Find spatial transformation T from one set X of reference points to another set $\hat{X}$.
  - Minimize squared distance between reference points.
- 6 degrees of freedom
  - Scale, X
  - Scale, Y
  - Translation, X
  - Translation, Y
  - Rotation
  - Skew

$$X \cdot T = \hat{X}$$

$$\begin{pmatrix} x_1 & y_1 & 1 \\ x_2 & y_2 & 1 \\ & . & \\ & . & \\ & . & \\ x_m & y_m & 1 \end{pmatrix} \cdot \begin{pmatrix} t_1 & t_2 & 0 \\ t_3 & t_4 & 0 \\ t_5 & t_6 & 1 \end{pmatrix} = \begin{pmatrix} \hat{x}_1 & \hat{y}_1 & 1 \\ \hat{x}_2 & \hat{y}_2 & 1 \\ & . & \\ & . & \\ & . & \\ \hat{x}_m & \hat{y}_m & 1 \end{pmatrix}$$



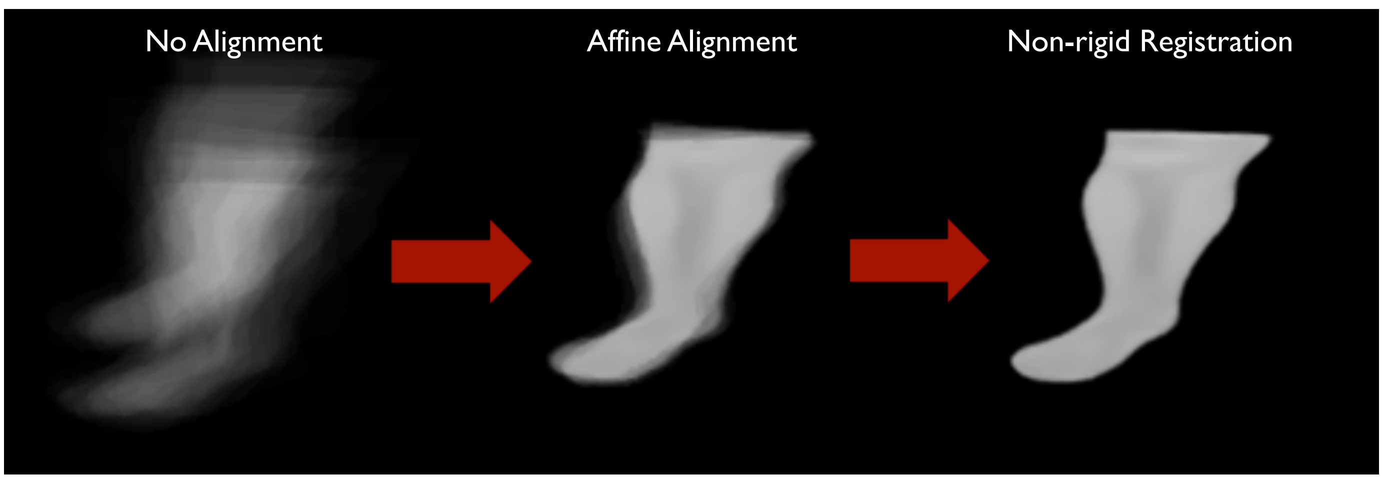
Affine Alignment



1. Pick arbitrary base image I_0
2. Find transformations T_i from I_0 to each image I_i
3. Find the mean transformation:
   $T_M = mean(\ \{T_i\}_{0 \leq i \leq m})$
4. Use T_M to align I_0 to mean coordinate space
5. Use $T_i^{-1} T_M$ to align I_i to mean coordinate space

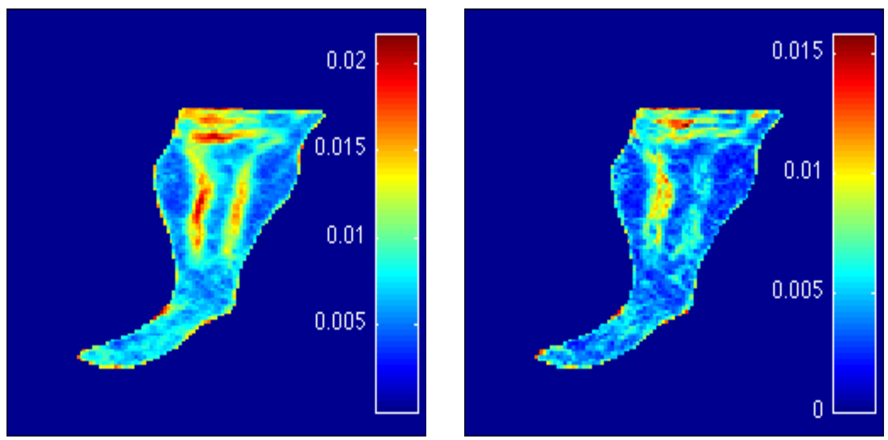
Non-Rigid Registration

- Eliminate differences in subject posture in specific regions
- Non-rigid, B-Spline Grid, Image Registration
  - Draw a grid over the image.
  - Deform the grid nonlinearly, so as to minimize squared pixel distance between the two images.
  - Use the deformed grid to move the original pixels into place.



Computing Training Image Statistics

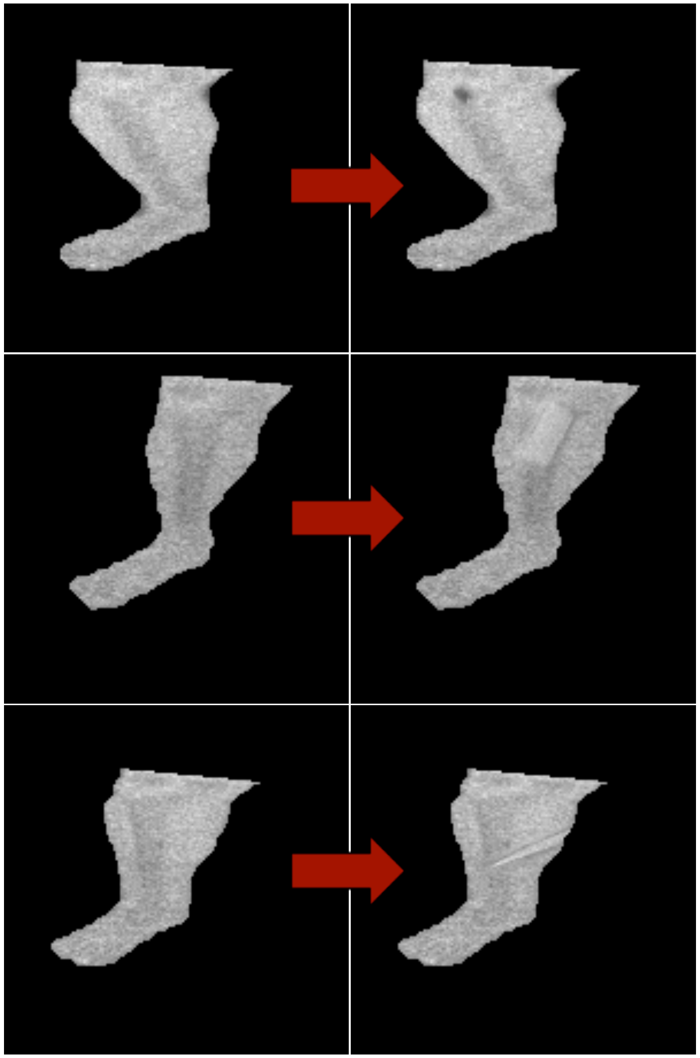
- Normalize intensities to range [0,1]
- Find gradient magnitude at each pixel
  - Simple first-order differences (vertical and horizontal)
- Compute mean and std. deviation across multiple images



(Left) Mean of gradient images.
(Right) Standard deviation of gradient images.

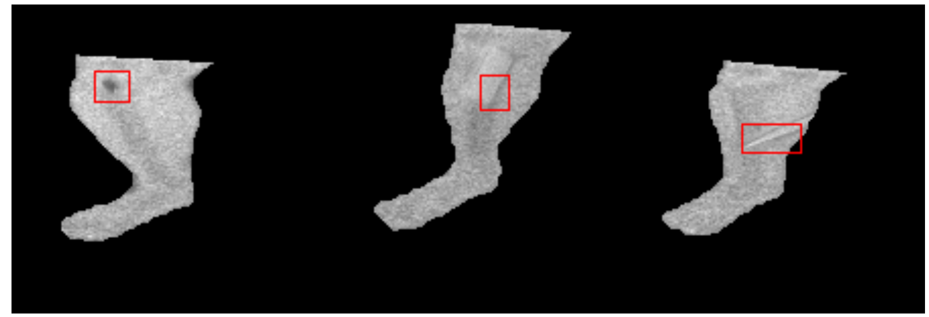
Creating a Set of Images for Testing

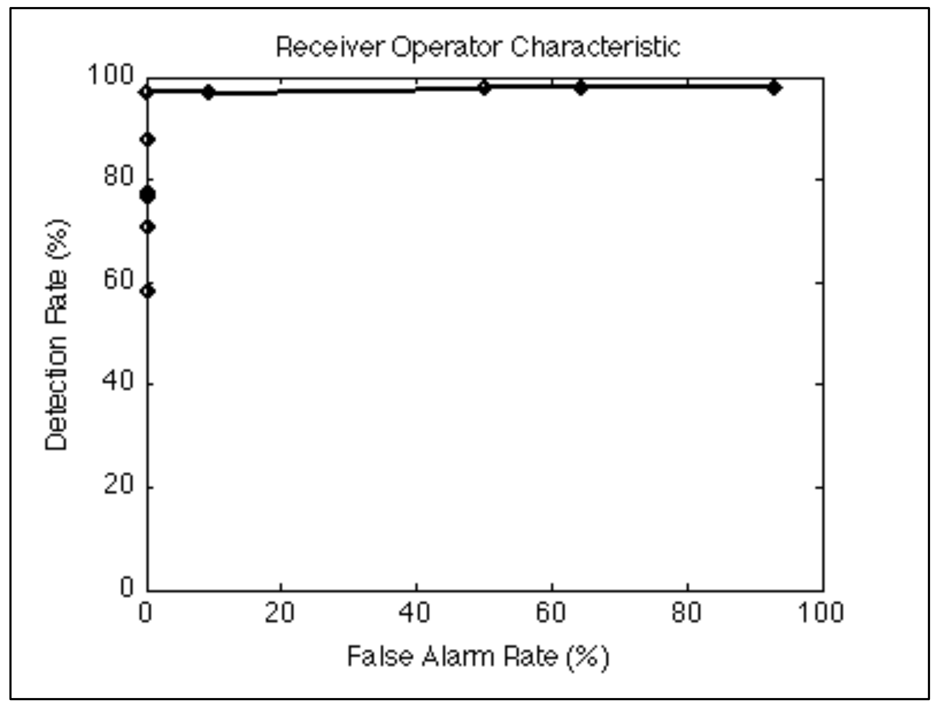
- Training data set
  - 14 left-leg images
  - No known anomalies
- Testing "live" data set
  - 22 right- and left-leg images
  - Distinct from training set
  - 4 known real anomalies
- Simulated anomalies
  - Crop real threats from full-body images; insert onto live images.
  - Randomize position, scale, rotation
  - Blend edges of inserted threat with surrounding leg area.



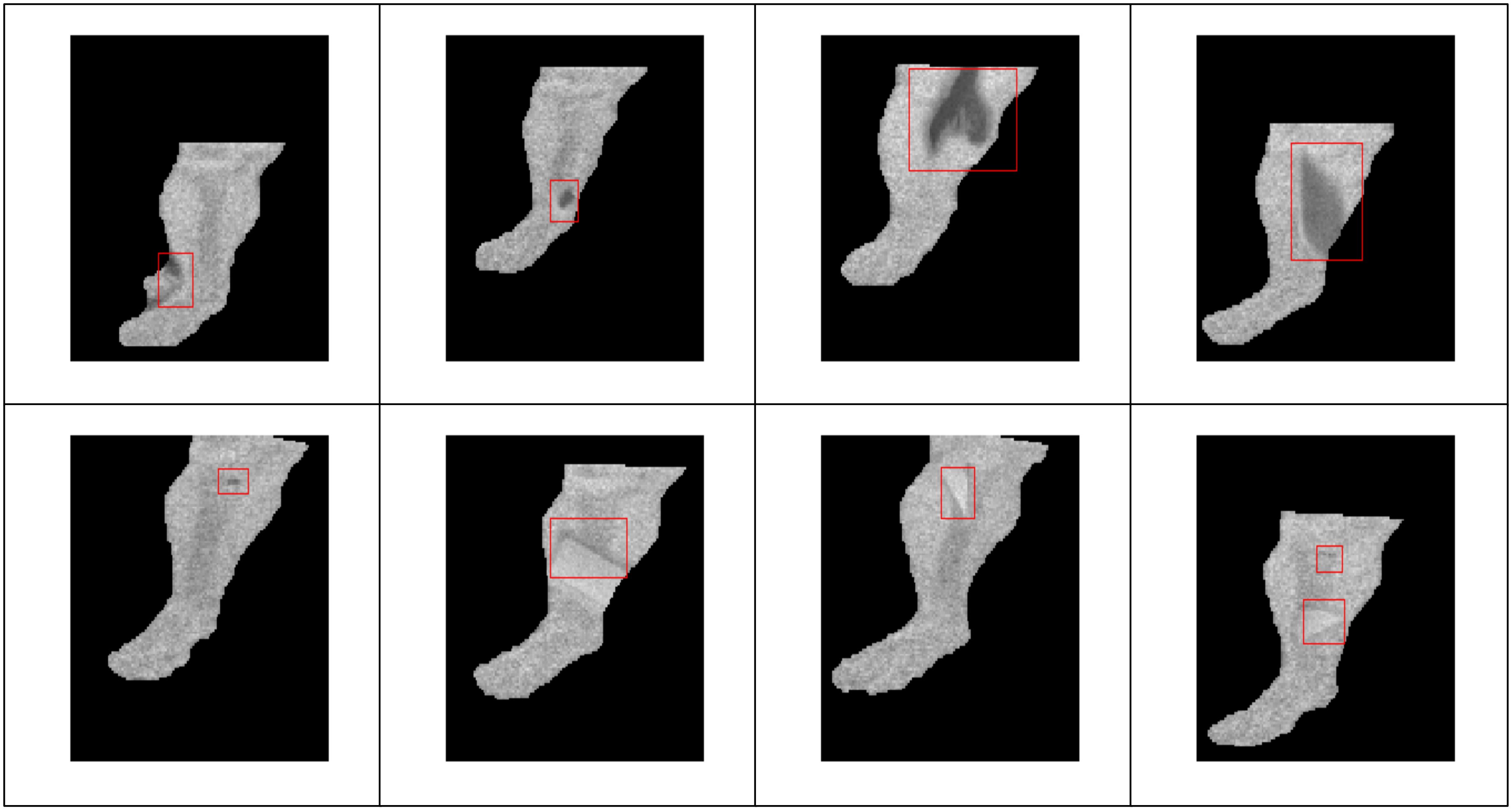
Detecting Anomalies in the Test Images

- Threshold gradient magnitudes at 13 standard deviations to get seed points
  - Chosen based on ROC curve
- Threshold at 7.5 standard deviations to find anomalous regions near the seed points
  - Chosen based on aesthetics

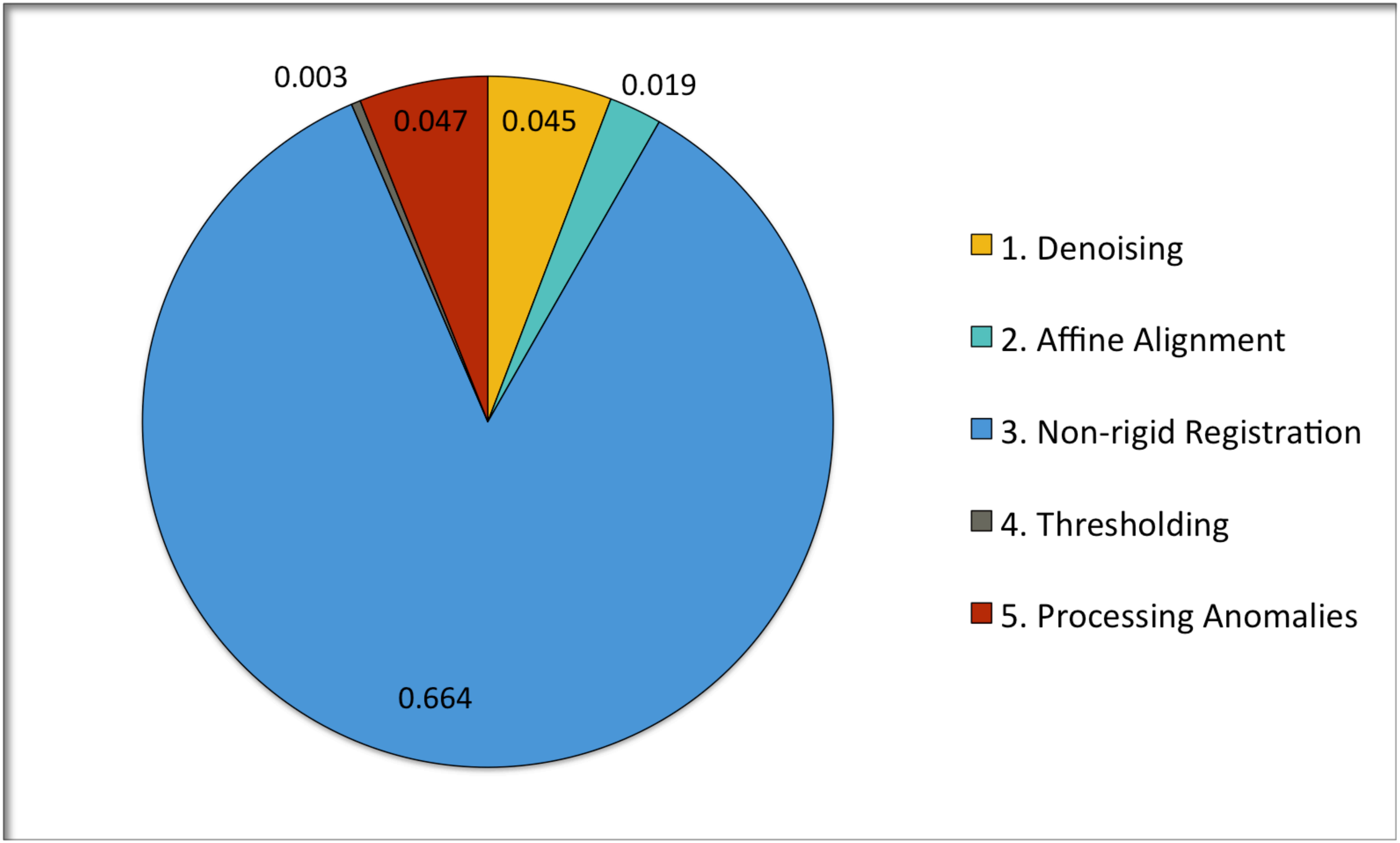




Detection Results



Time Breakdown of Algorithm (seconds)



Algorithm Performance

- Detection Rate: 97(±1)%
  - Def. – An anomaly was detected in an image that was known to contain an anomaly (real or simulated).
  - Real: 4/4
  - Simulated: 91/94 (over multiple runs)

- False-Alarm Rate: ~0% (0/22)
  - Def. – An anomaly was detected in an image that was not known to contain an anomaly.
  - Multiple test runs do not increase false-alarm rate precision.

Algorithm Limitations

- Limitations
  - Number of images – more training data increases robustness
  - High variance at borders necessitates ignoring border regions
  - Leg region needs to be manually cropped for each leg

- Future Work
  - Automatically crop the region of interest
  - Extend algorithm to work with other parts of the body (e.g. rear leg, upper leg)

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- **Special Thanks**

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