Lecture 24 – Medical Image Analysis

This lecture will cover: (*FMI: CH7-8*)

– Medical Imaging computing

– Visualization for diagnosis and therapy

Medical image computing

- Computer-assisted medical image analysis is developed due to
  - large amount of images per case
  - Need of objective, quantitative information from medical images.

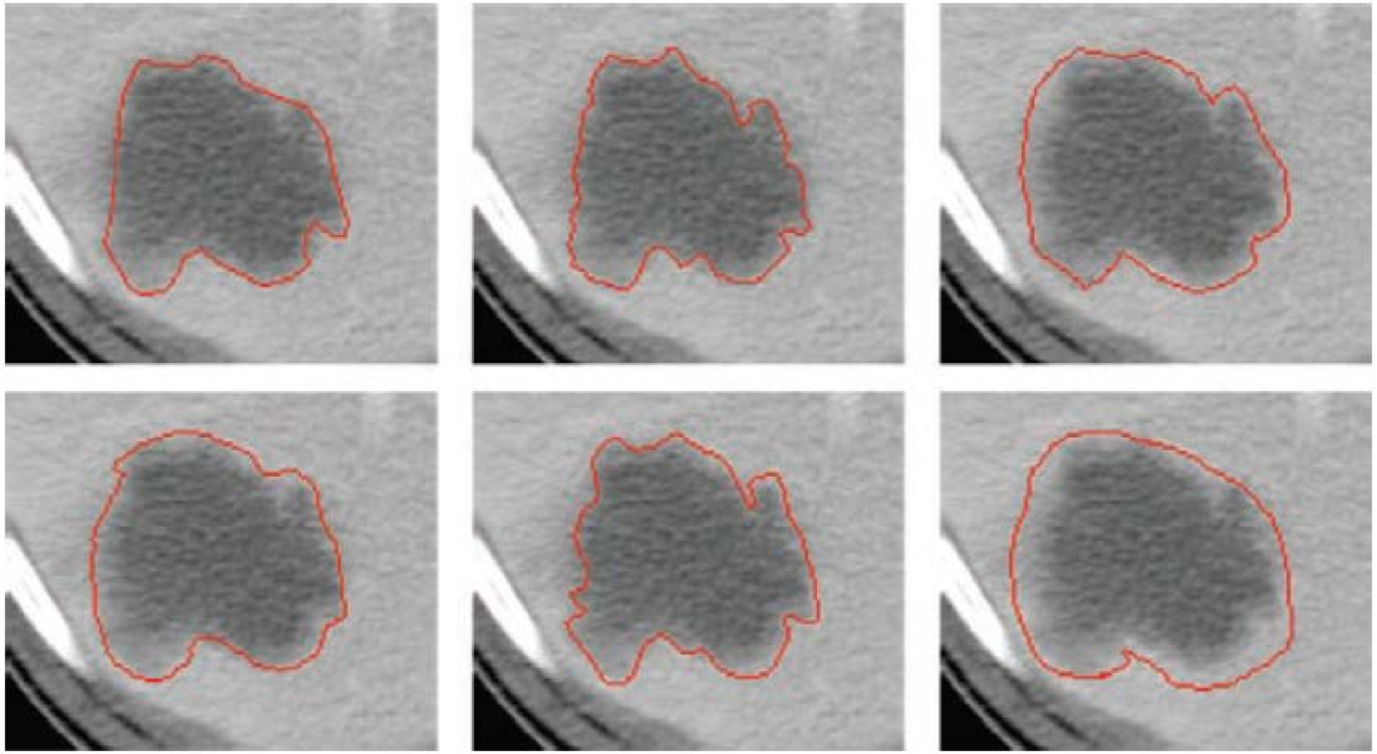
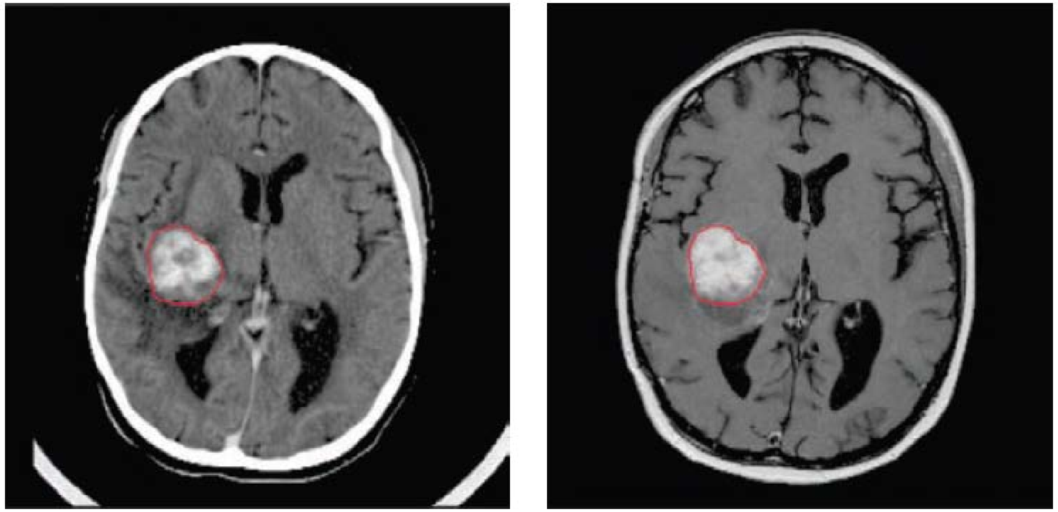


Fig. Impression of intra- and inter-observer variability of manual delineations of a lesion in a CT image of the liver. Three trained observers (two radiologists and one radiotherapist) delineated this lesion twice with an interval of about one week (upper row and bottom row, respectively). The area delineated varies up to 10‰ per observer, and the difference between observers amounts to more than 20‰..

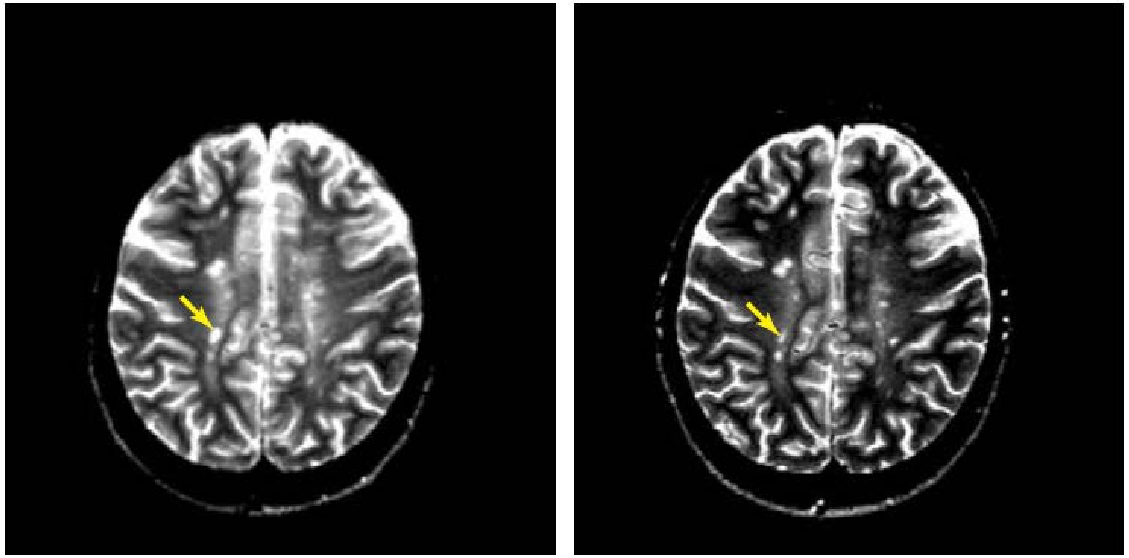
Automated image computing

- Complexity of the image data
- Complexity of the model and prototype
  - Multimodal analysis
  - Multitemporal analysis



(a) (b)

Fig. Medical image analysis often benefits from the ability to combine complementary information provided by multimodal images, as is illustrated here in the case of radiotherapy planning. (a) CT slice of the brain of a patient with a brain tumor. (b) MR image of the same patient that was reformatted after 3D registration of CT with MRI so that pixels at the same position in both images are anatomically identical. Although CT is needed for dose calculations, the lesion boundary can be located more accurately using MRI. After registration, the lesion was delineated in the MR image and the outline transferred to the CT image.



(a) (b)

Fig. In medical image analysis, it is often necessary to combine image information acquired at different moments in time. This example shows two T2-weighted MR images of the same multiple sclerosis (MS) patient acquired with a time interval of one year. Image (b) was resliced after proper registration with image (a) to compensate for differences in patient positioning in the scanner. After registration, corresponding pixels in both images refer to the same anatomical location in the patient and can straightforwardly be compared. This way the evolution of MS lesions over time can be accurately inspected (arrow).

Computational strategies

- **Prior knowledge to build a suitable model or prototype:**
  - Photometric features: intensity, color, gradient and texture;
  - Geometric features: pose, shape, deformation, motion, spatial relationships;
  - Contextual features: non-image related knowledge, i.e. clinical or genetic data;
- **Model-to-data tuning**
  - Low-level methods: region growing, edge detection
  - Model-based methods:
    - ✓ Data classification/regression:
      - pixel labeling: supervised and unsupervised learning,
      - pattern recognition
    - ✓ Model fitting:
      - Geometric modeling fitting using a transformation matrix;
      - Flexible geometric model fitting

Edge detection

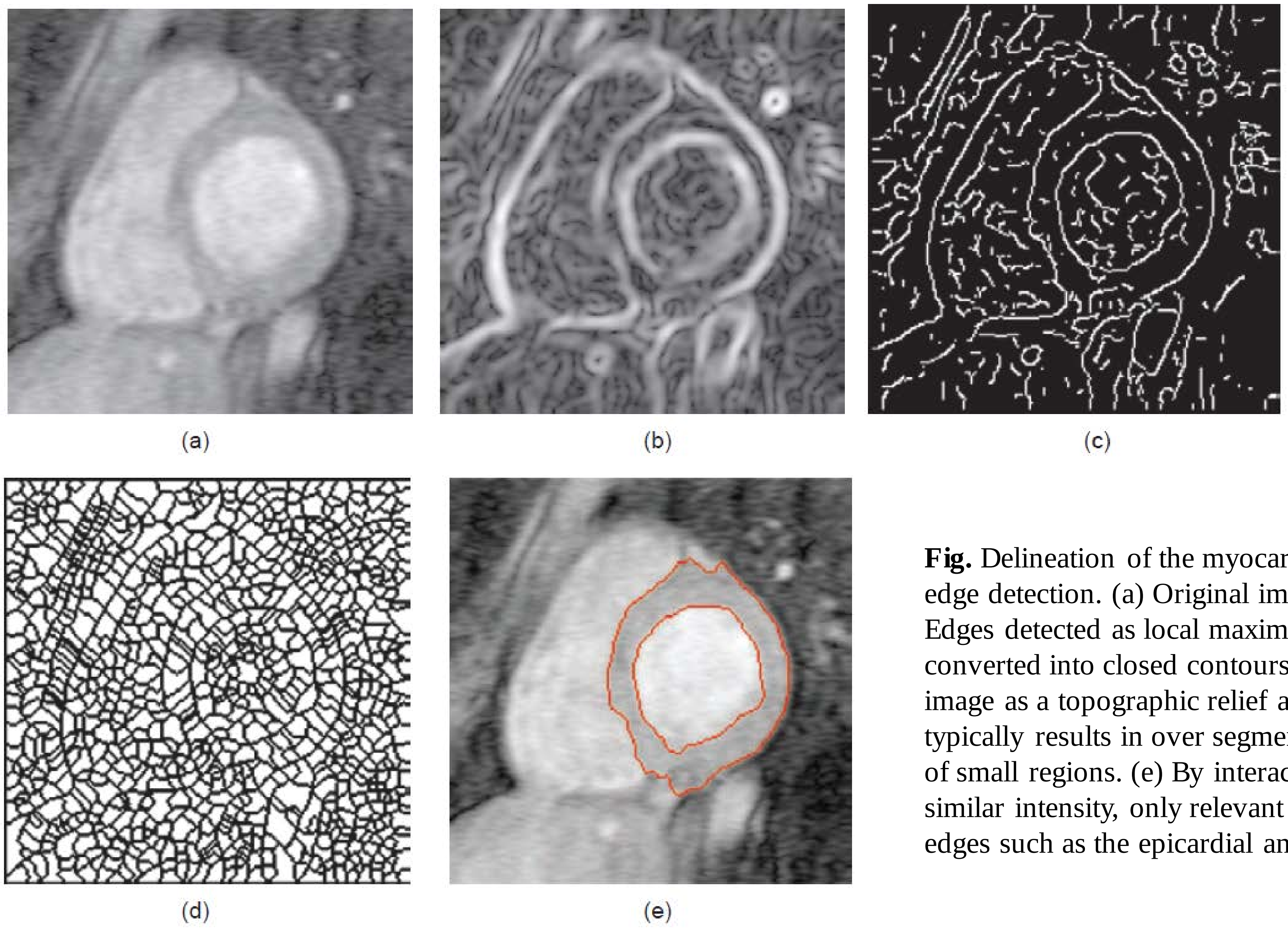


Fig. Delineation of the myocardial wall in an MR image of the heart by edge detection. (a) Original image. (b) Gradient magnitude image. (c) Edges detected as local maxima of the gradient magnitude. (d) Edges converted into closed contours by considering the gradient magnitude image as a topographic relief and computing watershed lines. This typically results in over segmentation of the image into a large number of small regions. (e) By interactively merging adjacent regions with similar intensity, only relevant boundaries corresponding to prominent edges such as the epicardial and endocardial borders remain.

Pixel labeling: supervised learning

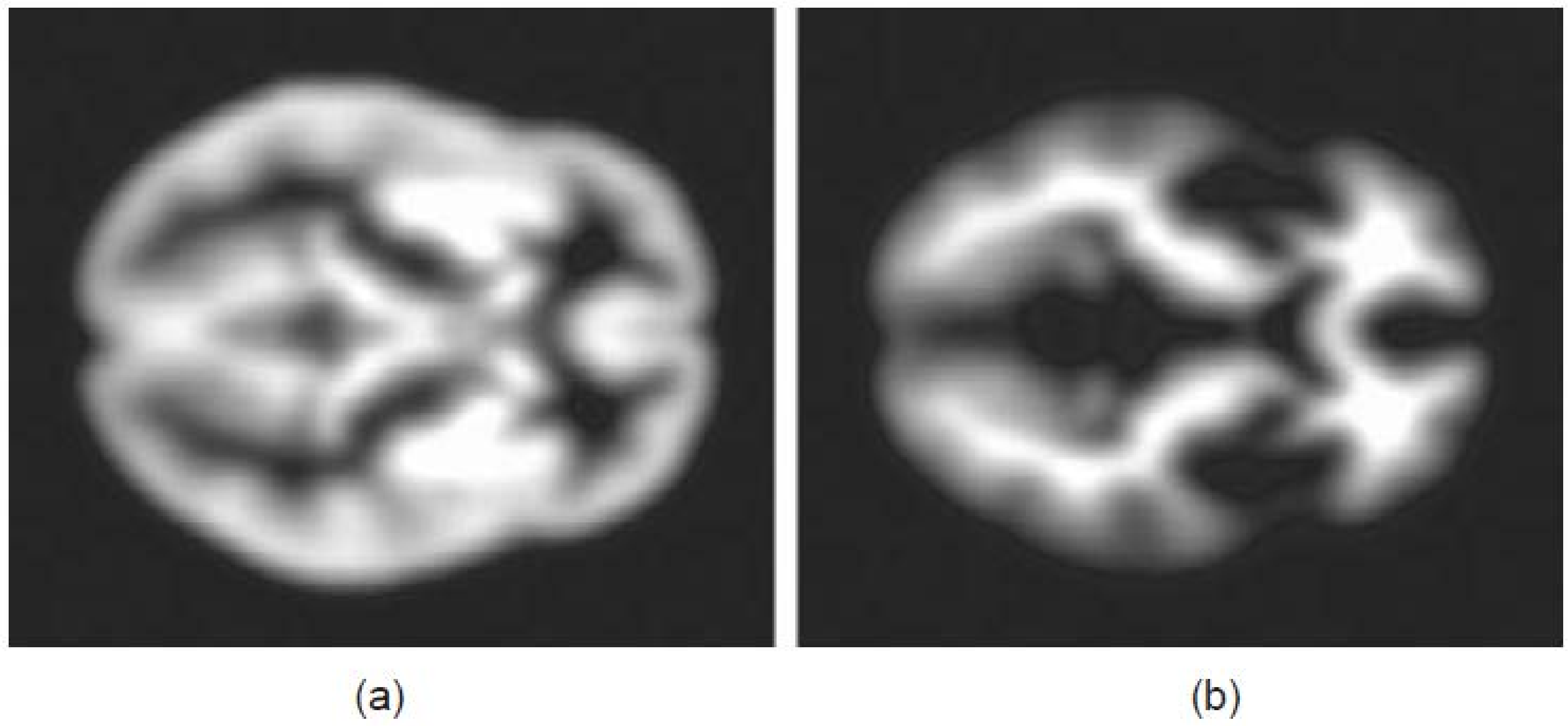


Fig. Statistical images of (a) the gray brain matter and (b) the white brain matter. The intensity in each pixel is proportional to its prior probability $p(\varphi_k = c_j)$ of belonging to that particular tissue class.

Pixel labeling: unsupervised learning

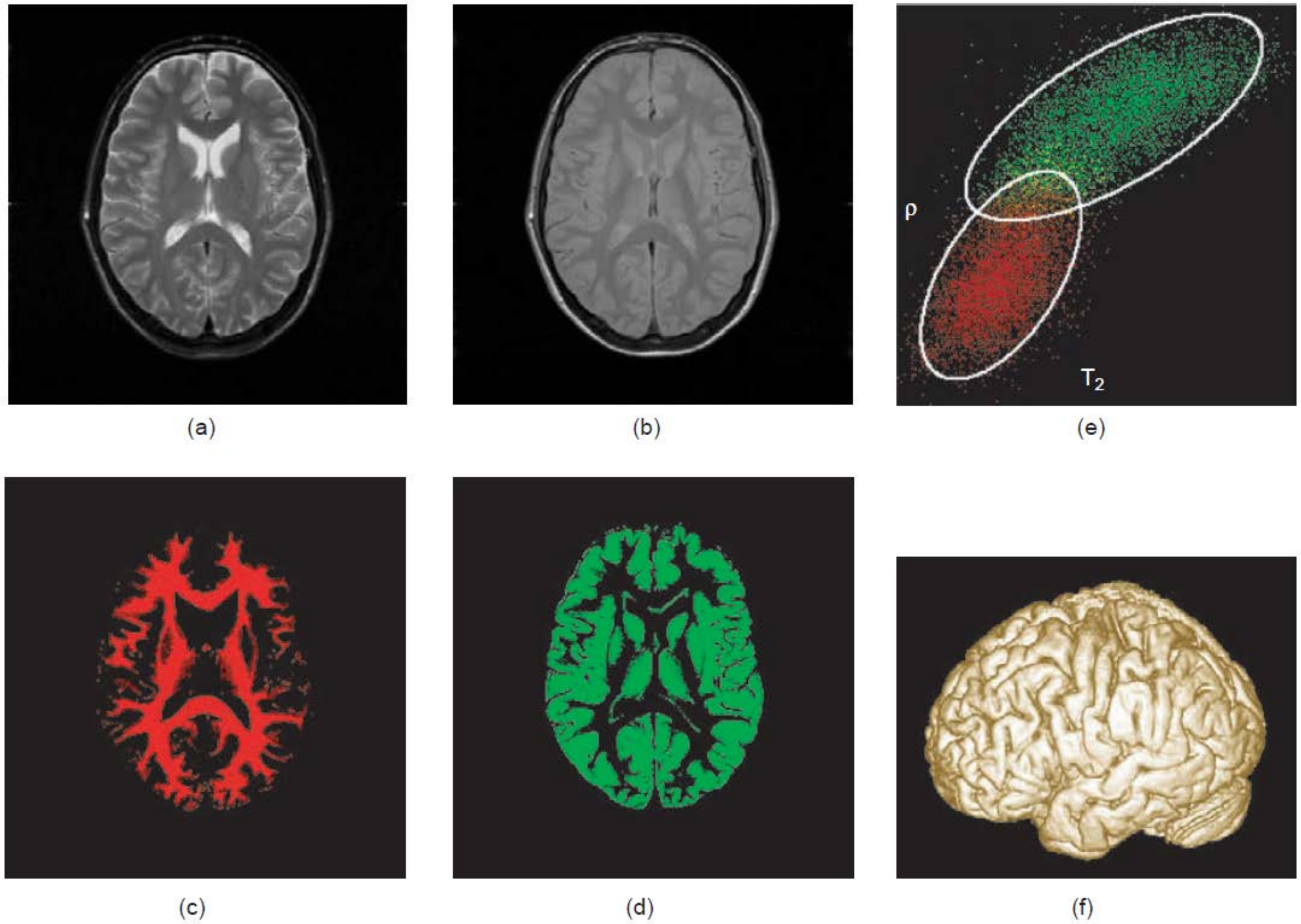


Fig. Brain tissue segmentation in multispectral MR images using unsupervised pixel classification. (a and b) Original T_2- and ρ-weighted MR images. (c and d) Classification of white and gray matter represented in red and green, respectively. (e) The probabilities for each point, shown in (c) and (d), are represented in a scatter plot as a function of ρ and T_2 together with the 0.99 percentile contours of the Gaussian class intensity model that was fitted using the EM algorithm. (f) 3D representation of the cortex obtained by volume rendering of the gray matter segmentation (d).

Fitting eigenimages

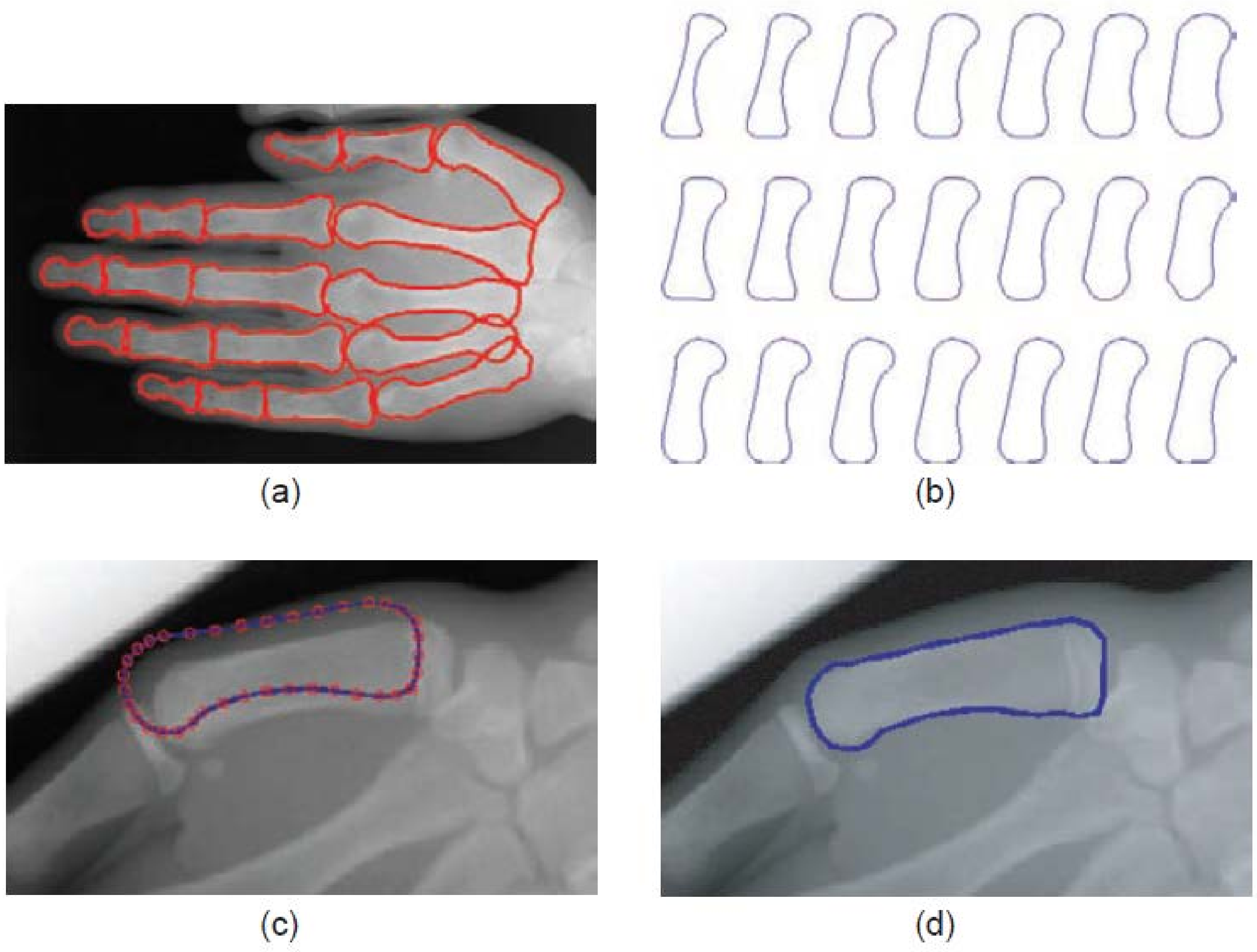


Fig. Active shape model for delineation of the finger bones in radiographic images. The result can be used to compare the shape of the bones to their normal shape in order to calculate the bone age of the patient. (a) Manual delineation of the bones. (b) Three principal modes of variation for the first metacarpal bone in a database of manually segmented training images. (c) The mean shape is put on top of a new image to initiate the optimization process. (d) Result of the optimization. While fitting the active shape model, the contour is displaced iteratively to match the intensity appearance observed in the training images with that along the contour.

Visualization for diagnosis and therapy

- **2D visualization**
- **3D rendering**
  - ✓ Surface rendering
  - ✓ Volume rendering
- **Virtual reality**
- **Intraoperative navigation**
- **Augmented reality**