Figure 2: Optimal dimension $d$ as a function of the Rician noise for three MR images in practice (Fabrigar et. al. (1999)). However, this method often overextracts components (Zwick and Velicer(1986)). Another commonly used approach is based on Cattell’s Scree test (Cattell(1966)), which involves the visual exploration of a graphical representation of the eigenvalues. This method has been criticized for its subjectivity, as there is no objective definition of the cutoff point between the important and trivial factors. Parallel analysis (Horn(1965)) is more accurate than the above methods for determining the number of retained components, but it tends to overextract components((Zwick and Velicer(1986)). Tasdizen(2009) proposed a modification of the parallel analysis algorithm for determining the number of components in PCA of image neighborhoods for denoising. One of the main drawbacks of parallel analysis is that the number of principal components to retain is highly dependent on the images and the noise. Therefore, different numbers of principal components are required for images with different features. A quick solution to this problem is to use a modified procedure for parallel analysis of ranked data. Let $\lambda_p$ for $1 \leq p \leq Q$ denote the eigenvalues of $C_R$ in Eq.(3.1) sorted in descending order. Similarly, let $\alpha_p$ denote the sorted eigenvalues of the artificial rank covariance matrix. Parallel analysis estimates data dimensionality as

$$d = \max\{|1 \leq p \leq Q| \lambda_p \geq \alpha_p\}.$$

Figure 2 shows the automatic dimensionality selection results for $brain$, $body$, and $knee$ images with noise $\sigma$ ranging from 5 to 50 in increments of 5. The numbers of significant components for PCA as shown in Figure 2 were computed as about 10, 14, and 16 for $brain$, $body$, and $knee$ images, respectively; however, the numbers of significant components for