INTRODUCTION: High angular resolution diffusion imaging (HARDI) is able to capture the water diffusion pattern in areas of complex intravoxel fiber configurations. However, compared to diffusion tensor imaging (DTI), HARDI adds extra complexity (e.g., high post-processing time and memory costs, nonintuitive visualization). Separating the data into Gaussian and non-Gaussian areas can allow using complex HARDI models just when it is necessary. We study HARDI anisotropy measures as classification criteria applied to different HARDI models. The chosen measures are fast to calculate and provide interactive data classification.

METHODS: We implemented several anisotropy measures from the literature, generalized anisotropy (GA)[1], generalized fractional anisotropy (GFA)[2], and the cumulative residual entropy (CRE)[3]. These measures were applied on the ADC profiles, analytical q-ball[4] and the DOT[1] all referred as spherical probability functions (SPFs). DOT has been adapted to be represented by real Spherical Harmonics, such that all anisotropy measures can be applied equally. To avoid the $R_0$ selection problem in DOT and inspired by definition of the Orientation Distribution Function (ODF) from Q-ball imaging [2] and the marginal ODF (mODF) from diffusion spectrum imaging (DSI)[5], we propose the similar ODFs computed from the DOT as: $\psi_{\text{DOT-ODF}}(r, \theta, \phi) = \int f_{\text{DOT-ODF}}(r, \theta, \phi) \, dr$, $\psi_{\text{DOT-mODF}}(r, \theta, \phi) = \int f_{\text{DOT-mODF}}(r, \theta, \phi) \, dr$, where $P(r, \theta, \phi)$ is the probability density function (PDF) computed from DOT and $R_{\text{max}}$ is set to a conservatively high value (see table on Figure 1 right). Furthermore, as a discrete binary measure for classification we propose to use the number of maxima (NM).

RESULTS: Phantom: DOT has the potential of recovering small angles regardless of the b-value, which we demonstrate in the table of Fig. 1. In the table we report the success at recovering two maxima in the crossing voxels by all of the examined SPFs. We observe that the derivations of the DOT (DOT-ODF and DOT-mODF) manifest similar behavior as the DOT itself, which shows a better angular resolution than q-ball and suggests a better choice of reconstruction algorithm for fiber tracking purpose. For the rest of the anisotropy measures, we can quantitatively describe the classification power of the 45° and 90° phantoms by using a binary classification statistical test. We report the specificity and sensitivity of the classified crossing and linear voxels respectively. Two thresholds are needed to separate the interval of anisotropy values into three distinct compartments: Isotropic/noise, Gaussian and non-Gaussian. We thus iterate over the whole range of values of each anisotropy measure and find the interval where all the crossings are detected while the number of false positives stays minimal. For the purpose of data simplification, the presence of false negatives is dangerous (i.e. crossings detected as linear), because relevant information can be lost. Therefore to ensure absence of false negatives, we set the sensitivity of crossing classification criteria to 1. In Fig. 1, bottom, we present the specificity of the crossing classification for each measure and the sensitivity of the linear detected voxels for the 45° and 90° phantoms respectively. Any measure with high specificity is a good candidate for classifying the crossing regions. Human: The centrum semiovale was used to illustrate the qualitative analysis of the classification results (Fig. 2). We applied the same classification measures as for the phantom study on the original and denoised data from our datasets. Denoising improves the glyph profiles and the coherence of the non-Gaussian regions, as seen in Fig. 2. We also observe a decrease in the irregularities in the crossing profiles. Going to very high b-values (i.e. $>$2000s/mm²) and modeling the data with high SH order ($>$4) results in polluted glyphs regardless with or without a denoising phase. Comparing the results of the classification from different measures, we observe that increasing the b-value sharpens the HARDI profiles and benefits only for maxima extraction purposes. However, there is no significant gain in classification of non-Gaussian profiles, as observed in the phantom study.

CONCLUSION: From our ex-vivo phantom study, we can conclude that CRE, GA and GFA can be applied as a reliable classification between Gaussian and non-Gaussian profiles with in general less than 8% false positive classification results in any configuration. GA and GFA have advantage over CRE since they can be modeled with a simple diffusion tensor. This classification can reduce the post-processing time and considerably accelerate the visualization of the data. Therefore, this has a potential benefit in clinical settings.