In recent years, low-rank based tensor completion, which is a higher order extension of matrix completion, has received considerable attention. However, the low-rank assumption is not sufficient for the recovery of visual data, such as color and 3D images, when the ratio of missing data is extremely high. In this paper, we consider “smoothness” constraints as well as low-rank approximations and propose an efficient algorithm for performing tensor completion that is particularly powerful regarding visual data. The proposed method admits significant advantages, owing to the integration of smooth PARAFAC decomposition for incomplete tensors and the efficient selection of models in order to minimize the tensor rank. Thus, our proposed method is termed as “smooth PARAFAC tensor completion (SPC).” In order to impose the smoothness constraints, we employ two strategies, total variation (SPC-TV) and quadratic variation (SPC-QV), and invoke the corresponding algorithms for model learning. Extensive experimental evaluations on both synthetic and real-world visual data illustrate the significant improvements of our method, in terms of both prediction performance and efficiency, compared with many state-of-the-art tensor completion methods.