

Gigapixel abundant-channel (**GIANT**) Image Analysis: Definition, Applications, and Challenges

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1 Definition

Image resolution and the number of channels are two critical attributes that dictate the size and complexity of an image. In this context, we introduce a category of images known as **GIANT** (GIgapixel AboundaNT-channel) images. Each image within this definition possesses **a minimum of one billion pixels** (Giga-pixels) and **exceeds five channels** (surpassing conventional camera/microscope images).

2 Applications

GIANT images are primarily obtained using advanced imaging technologies, such as high-dimensional virtual microscopy [1, 2], which enable the capture of a comprehensive range of information. Examples of such images include, but are not limited to, multi-channel whole slide images (WSI) [3, 4], multiplex immunofluorescence (MxIF) images [5, 6], high-resolution fluorescence in situ hybridization (FISH) images [7, 8], and sophisticated spatial transcriptomics (ST) images [9, 10] (**Fig. 1**). These GIANT images are proficient in recording an extensive array of data, encompassing multiple color channels, depth information, and other data types like temperature, metabolic activity, or gene expression profiles.

GIANT images are widely applicable in fundamental scientific research, particularly in disciplines like biology [11, 12], medicine [13, 14], materials science [15, 16], and remote sensing [17, 18]. Microscopic images facilitate the examination of intricate biological systems and the composition of materials, while remote sensing generates high-resolution satellite imagery. For example, the GIANT images permit the visualization of thousands of genes at the subcellular level with single-molecule sensitivity and gigapixel resolution, offering unparalleled spatial information [19].

3 Challenges

Despite their numerous advantages, processing GIANT images presents several significant challenges, including but are not limited to:

Sensing & Image Processing: Acquiring GIANT images entails ensuring that the various channels and layers of the image are precisely aligned with one another, which can be a computationally demanding task. Moreover, the ultra-high resolution and abundant channel characteristics of GIANT images introduce considerable computational difficulties to fundamental image processing tasks, such as deconvolution and denoising.

Scalable Learning: The immense size and high resolution of GIANT images lead to extended processing durations. For example, implementing deep learning-based image computation on a single gigapixel image may take several hours or even days to complete.

Computing Cyberinfrastructure: The processing of GIANT images generally requires formidable computing resources, including advanced GPUs, high-performance computing clusters, or cloud computing platforms. Procuring and operating these resources can be expensive and may call for specialized expertise to ensure efficient setup and usage.

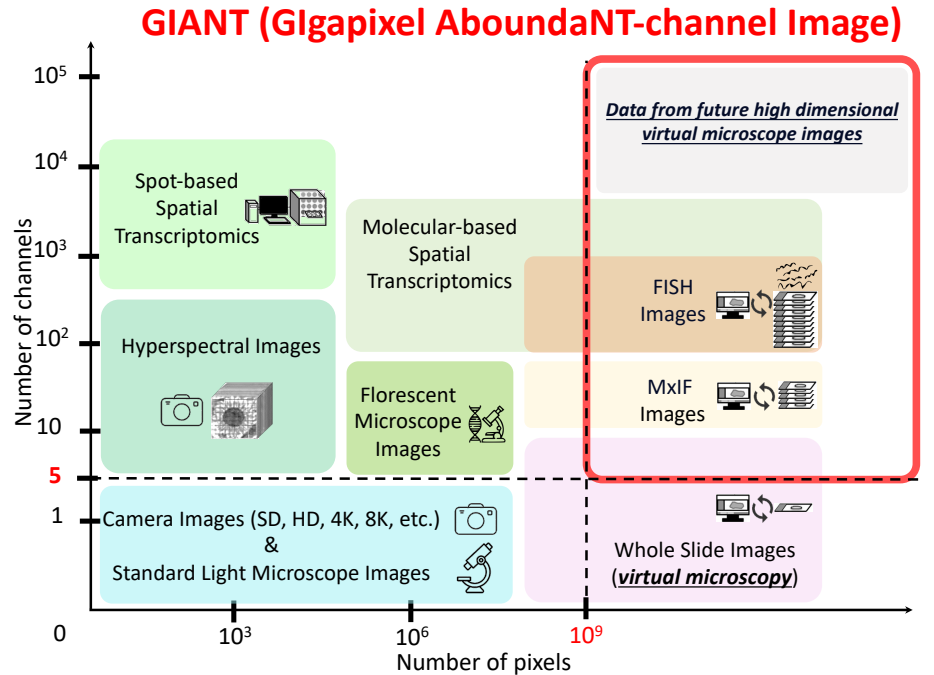


Figure 1: Definition of the GIANT image.

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