In the scanning transmission electron microscope (STEM), there are many uses of image-series including; frame-averaging to improve signal-noise ratios, focal-series for optical-sectioning experiments / aberration studies, time-series to study dynamic processes like beam-damage, or camera-length series to study strain effects. However, at typical STEM acquisition times, stage / sample drift and low frequency distortions can become apparent. For quantitative interpretation we must correct these using rigid and non-rigid registration respectively. Recently we have developed an improved and automated registration method, customised for the challenges unique to STEM. Three modifications to the mutual-correlation function (MCF) method [1] have been designed, to specifically address problems registering images that include large areas of crystalline material, defects or edges.

Firstly, the user is able to vary the power on the MCF normalisation, changing the relative weighting of the crystal lattice in the image, between 0 (no normalisation, simple cross-correlation) and 1 (all spacings weighted equally, phase-correlation). Generally an intermediate value ≈0.4–0.75 is optimum (Fig 1, left); where crystalline information is used to provide an accurate registration but not relied upon, as this could easily introduce unit-cell ‘hops’ leading to mis-registration.

Secondly, as there are often multiple possible vectors identified when registering lattice images an iterative ‘learning mode’ has been introduced. With this option enabled the algorithm will try to iteratively learn the global drift rate. This is especially useful for time-series or focal-series data where the time between frames, and drift rate, is fairly constant. Fig 1 (right) shows an example annular dark-field STEM focal-series registered both with and without this new mode. With learning mode disabled, characteristic unit cell ‘hops’ were observed (dashed lines). While the registered images may appear reasonable, this diagnosed stage drift is not physically real. With learning mode enabled the consistent smooth drift rate is correctly determined.

Thirdly, as diagnosing non-rigid offsets can be challenging near sample edges or defects (Fig 2, middle) the user may optionally ‘lock’ the diagnosed offset vectors together in the fast scan direction (Fig 2, right). This prevents the introduction of artefacts at edges or defects whilst still allowing for effective non-rigid registration of STEM data. Together, these refinements significantly reduce the risk of ‘crystal hops’ during rigid registration and of artefact introduction during non-rigid registration improving both the throughput and precision of automated STEM data analysis.

Fig. 1: Enlargement of the central region of an example mutual-correlation function (MCF) with peaks indicating probability of image-pair offset matches (left) and right the rigid-registration results with and without the optional ‘learning mode’ (see text).

Fig. 2: Part of the non-rigid registration stage of a HAADF time-series data-set of a [110] oriented SrTiO3 nano-cube (left). The non-rigid displacement map for the y-direction is shown with pixels allowed to move freely (centre) and with the fast-scan rows locked to move together (right).