



Fig. 6.2: **Image similarity via ensemble clustering.** Different trees (whose leaves are denoted by different colour curves) induce different image partitions. The red tree yields the partition  $\{\{a, b, c, d\}, \{e, f\}, \{g, h\}\}$ . The green tree yields the partition  $\{\{a, b, c\}, \{d, e, f\}, \{g, h\}\}$ . The overlap between clusters in different trees is captured mathematically by the forest affinity matrix  $W$ . In  $W$  we will have that image  $e$  is closer to image  $c$  than to image  $g$ . Therefore, ensemble-based clustering induces data affinity. See text for details.

**Computational efficiency.** In this algorithm the bottleneck is the solution of the eigen-system (6.7) which could be slow for a large number of input points  $k$ . However, in (6.9) only the  $d' \ll k$  bottom eigenvectors are necessary. This, in conjunction with the fact that the matrix  $L$  is usually very sparse (especially for the binary affinity model) can yield efficient implementations. Please note that only one eigen-system