The computation of the eigenvalue decomposition (EVD) for a matrix $W W^T$ can become computationally prohibitive when the matrix size becomes large, typically exceeding a few thousand rows or columns. This is because the standard algorithm for EVD, the Jacobi eigenvalue algorithm, scales cubically with the matrix size, making it impractical for large matrices.

To address this challenge, several alternatives have been developed that offer reduced computational complexity. One approach is Krylov subspace methods, such as the Lanczos algorithm, which scale quadratically with the matrix size. These methods are more efficient for large matrices but may require more iterations to converge.

Another approach is approximate EVD, which aims to find approximate eigenvalues and eigenvectors of the matrix. This can be achieved using techniques such as power iteration or random sampling, which can be significantly faster than standard EVD for large matrices. However, the accuracy of the approximations may be limited.

In summary, the computational cost of EVD for the matrix $W W^T$ grows rapidly with matrix size, making it impractical for large matrices. Alternative methods such as Krylov subspace methods and approximate EVD can offer improved efficiency but may sacrifice accuracy or require more iterations. The choice of method depends on the specific application and the desired accuracy and computational resources.