**ABSTRACT**

**Motivation:** Cryo-electron microscopy (cryo-EM) is a widely-used technology for ultrastructure determination, which constructs the three-dimensional (3D) structures of protein and macromolecular complex from a set of two-dimensional (2D) micrographs. However, limited by the electron beam dose, the micrographs in cryo-EM generally suffer from extremely low signal-to-noise ratio (SNR), which hampers the efficiency and effectiveness of downstream analysis. Especially, the noise in cryo-EM is not simple additive or multiplicative noise whose statistical characteristics are quite different from the ones in natural image, extremely shocking the performance of conventional denoising methods.

**Results:** Here, we introduce the Noise-Transfer2Clean (NT2C), a denoising deep neural network (DNN) for cryo-EM to enhance image contrast and restore specimen signal, whose main idea is to improve the denoising performance by correctly discovering the noise model of cryo-EM images and transferring the statistical nature of noise into the denoiser. Especially, to cope with the complex noise model in cryo-EM, we design a contrast-guided noise and signal re-weighted algorithm to achieve clean-noisy data synthesis and data augmentation, making our method authentically achieve signal restoration based on noise’s true properties. To our knowledge, NT2C is the first denoising method that resolves the complex noise model in cryo-EM images. Comprehensive experimental results on simulated datasets and real datasets show that NT2C achieved a notable improvement in image denoising and specimen signal restoration, comparing with the state-of-art methods. A real-world case study shows that NT2C can improve the recognition rate on hard-to-identify particles by 19% in the particle picking task.

**1 INTRODUCTION**

Cryo-electron microscopy (cryo-EM) is a widely-used technology that resolves high-resolution three-dimensional (3D) structures of protein and macromolecular complexes from a series of two-dimensional (2D) micrographs (Bai et al., 2015). However, the signal-to-noise ratio (SNR) of raw cryo-EM images is estimated to be only as high as 0.01–0.1 (Bendory et al., 2020), amongst the lowest in any imaging field. Most of the image restoration algorithms are not easily applicable to cryo-EM images. For an image restoration algorithm, it is usually necessary to know the structure of the object before picking, segmentation, and other image analysis processes to attain high-resolution cryo-EM 3D reconstructions.

A variety of conventional methods have been developed to improve the contrast and decrease the noise level in cryo-EM micrographs, such as BM3D (Dabov et al., 2007), band-pass filter (Penczek et al., 2010) and Wiener filter (Sindelar et al., 2011). For an image restoration algorithm, additional image prior knowledge will be introduced to repair the missing and degenerated information, in which human knowledge concluded from the natural images are usually used. However, the noise model in cryo-EM micrograph is usually unknown and varies in different data collection configurations. Therefore, the pre-defined image priors used in these conventional methods cannot correctly fit the noise model in cryo-EM, leading to a limited performance when the conventional methods are applied to cryo-EM data.

Recently, learning-based denoising methods have shown their advantages. Mao et al., 2016 proposed an encoding-decoding framework with symmetric convolutional-deconvolutional layers for image restoration. Ledig et al., 2017 presented a generative adversarial network (GAN) for image super-resolution (SR) which recovers photo-realistic textures from heavily downsampled images. However, most of these learning methods require a clean-noisy paired dataset for training, therefore, can not be applied to cryo-EM, where ground truth is unavailable. To overcome this barrier, several methods like Bepler et al., 2020 proposed a denoiser called Topaz-Denoise for cryo-EM and cryo-ET, based on an N2N architecture and trained by thousands of cryo-EM micrographs.

In this paper, we propose a novel denoising framework, the Noise-Transfer2Clean (NT2C), to restore the specimen signal and enhance the image contrast by discovering the unknown noise model from the cryo-EM image. Firstly, a coarse CNN denoiser is trained to enhance the contrast of a cryo-EM image, to distinguish the background and specimen signal. Then, the pure noise patches are extracted from the micrographs and fed into a GAN to estimate and simulate the noise distribution. Finally, a fine denoising network is able to be trained by the clean-noisy pairs simulated from the accurately estimated noise distribution in GAN. By resolving the noise model in a cryo-EM image, our strategy is able to further decompress the specimen signal from the noisy background. Especially, to cope with the complex noise model in cryo-EM, we design a contrast-guided noise and signal re-weighted algorithm to achieve clean-noisy data synthesis and data augmentation, making our method authentically achieve signal restoration based on the noise’s true properties. We have tested and compared our denoising model with several commonly-used cryo-EM denoising algorithms on both synthetic and real datasets. The experiment results on synthetic datasets show NT2C’s denoising performance is comparable to current state-of-the-art methods; and the results on three real datasets demonstrate NT2C’s ability to deal with real-world high-noise-level cryo-EM images. A case study on particle picking further proves that our denoising method
is able to restore very weak particle signals, improving the recognition rate on hard-to-identify particles by 19%.

2 THE IMAGING MODEL IN CRYO-EM

The imaging process in cryo-EM involves the conversion of the electron wave’s intensity distribution into a digital signal via a detector (Vulovic et al., 2013), which introduces multiple complex noises to the final micrographs. According to the principle of cryo-EM, the detected image can be written as

\[ I(x, y) = I_{\text{真}} + I_{\text{暗}} + CF \cdot F^{-1} \left[ P_{\text{noise}} \left( \Phi_x \cdot F^{-1} \left[ f_0(q) \sqrt{\text{DQE}(q)} \right] \right) \cdot \text{NTF}(q) \right] \]

where \( f_0(q) \) is the Fourier spectrum of the noise-free signal, \( \text{DQE} \) is the detective quantum efficiency, \( \Phi_x \) is the incident electron flux in \( [e^- / \text{area}] \), \( F \) is Fourier transform, \( F^{-1} \) is inverse Fourier transform, \( P_{\text{noise}} \) is the Poisson described shot noise, \( \text{NTF} \) is the noise transfer function, \( CF \) is a scale factor for detectors, \( I_{\text{真}} \) indicates the readout noise and \( I_{\text{暗}} \) indicates the dark current of detector. The detective quantum efficiency \( \text{DQE} \) is defined as \( \text{DQE}(q) = \text{MTF}^2(q) / \text{NTF}^2(q) \), where \( \text{MTF}^2(q) = \text{NPS}_{\text{raw}} / (CF^2 \Phi_x) \) with \( \text{NPS} \) being the noise power spectrum and \( \text{MTF} \) describes transfer of the signal amplitude for different spatial frequencies. As described in the formula, the signal propagation can be modeled as follows: (1) \( I_{\text{真}}(q) \) is damped (multiplied) by the ratio between signal (\( \text{MTF} \)) and noise (\( \text{NTF} \)) transfer, (2) the signal is multiplied by the integrated electron flux and shot noise contributions are added, (3) the Fourier spectrum of that noisy signal is damped by the \( \text{NTF} \), (4) the number of electrons are scaled to the image gray values in detector analog-to-digital unit [ADU]. Therefore, the noise in cryo-EM comes from three aspects: the shot noise contributions added in the measurement process; the readout noise \( I_{\text{真}} \) and dark current \( I_{\text{暗}} \) from the detector; blurring effect caused by detector point spread function PSF \( (x,y) \) whose Fourier transform is the MTF.

3 METHODS

3.1 NT2C protocol

3.1.1 Overview of the procedure

The key idea of NT2C is discovering the noise model of cryo-EM images over pure noise patches and transferring the statistical nature of noise into the denoiser. As shown in Figure 1, NT2C contains three modules:

(a) Noise extraction. The noise extraction module takes raw micrographs as input, and output the pure noise patches of the background (see subsection 3.2.2). Due to the extremely low SNR in cryo-EM micrographs, distinguishing the background from the particles is a hard task in raw noisy micrographs. Here, a coarse denoiser (see subsection 3.1.2) is trained to roughly enhance the image quality and aid the extraction of noise patches, based on the simulated datasets with the same experimental parameters (see subsection 3.2.1).

(b) Noise modeling. The statistical properties of noise in cryo-EM micrograph change with different configurations during data collection. It is critical to correctly understand the statistical nature of the noise for image denoising. Here, a GAN noise synthesizer (see subsection 3.1.2) is trained to learn the statistical properties of noise, with pure noise patches as input and simulated noise patches as output.

(c) Denoiser training. The noise synthesizer poses the possibility of clean-noisy pair generation for cryo-EM, which is critical in denoiser training. However, as described in section 2, the noise pattern in cryo-EM is quite complex. Here, we design a contrast-guided noise and signal re-weighted algorithm (see subsection 3.2.3) to transfer the non-additive noise to a clean image, to achieve clean-noisy pair synthesis and data augmentation. Based on the abundant synthesized clean-noisy pairs, a fine denoiser (see subsection 3.1.2) is able to be trained to precisely restore specimen signal from the high-level noise.

3.1.2 Main components

1) CNN denoiser

The CNN denoiser in NT2C is based on a U-net architecture (Ronneberger et al., 2015), which contains five max-pooling down-sampling blocks and five nearest-neighbor up-sampling blocks, with skip connections between down- and up-sampling blocks at each spatial resolution (shown in Figure 2). Given the set of clean-noisy pairs \( \{(\mathbf{x}, \mathbf{y}) \} \), a denoising function \( f \) with parameter \( \theta \) can be learned. The loss function for our task is

\[ \arg\min_{\theta} E_{\mathbf{x}, \mathbf{y}} \left[ \| f_0(x) - y \|_p \right] \]

where \( p = 2 \) is used in NT2C to find \( f \) with mean-seeking behavior.

The CNN denoiser has been called twice in NT2C’s procedure: (i) as a coarse denoiser trained with the simulated clean-noisy pairs (see subsection 3.2.1) to roughly enhance the contrast of cryo-EM images, for the ease of noise patch extraction; (ii) as a fine denoiser trained with the clean-noisy pairs produced by the noise and signal re-weighted algorithm (see GAN noise synthesizer and subsection 3.2.3) to capture the nature of noise statistical properties and restore the specimen signal in cryo-EM micrographs. Here, the model parameters of the coarse denoiser could be transferred to the fine denoiser to avoid retrain from scratch.

2) GAN noise synthesizer

The noise model in cryo-EM is too complex to be explicitly described by an analytical expression. Here, the improved GAN framework (Gulrajani et al., 2017) is adopted to implicitly learn the latent noise model in cryo-EM micrographs. This framework contains two components, a generative network that consists of five fully connected layers, and a discriminative network which consists of three full connected layers (shown in Figure 3). Batch Normalization (Ioffe et al., 2015) is used in the generator to secure...
the model stability and Leaky Rectified Linear Unit (LeakyReLU) (Maas et al., 2013) activation is used in both the generator and the discriminator to ensure fast learning.

The generative network is trained to generate noise samples, while the discriminative network is trained to determine whether a noise sample is from real data or the generative network.

The generative network is trained to generate noise samples while the discriminative network is trained to determine whether a sample is from real data or the generative network. After the convergence of adversarial learning, the generative network will be able to produce noise patches hard to be distinguished from real noise patches. The loss function for our task is

$$L_{GAN} = E_{x \sim \mathcal{P}_r} [D(x)] - E_{z \sim \mathcal{P}_g} [D(z)] + \lambda E_{z \sim \mathcal{P}_g} [\|\nabla_D D(x)\|_2 - 1]^2$$

where \(\mathcal{P}_r\) is the distribution over noise patches, \(\mathcal{P}_g\) is the generator distribution, \(\mathcal{P}_f\) is defined as a distribution of samples uniformly along straight lines between pairs of points sampled from \(\mathcal{P}_r\) and \(\mathcal{P}_g\).

### 3.2 Detailed algorithm

#### 3.2.1 Simulation based on experimental parameters

The lack of supervised training data hampers the application of learning-based denoising method in cryo-EM. Here, we adopt the simulation software InSilicoTEM (Vulovic et al., 2013) to generate paired cleanliness datasets, which can simulate the photographing process in cryo-EM based on physical principles.

We set the simulation according to the experimental parameters used in data collection (shown in Figure 4), including the pixel size, defocus, voltage, electron dose, and detector type, which make the limited resolution, contrast transfer function (Wade et al., 1992) and modulation in the simulation very close to the real-world data. The homologous proteins with similar size downloaded from Protein Data Bank (PDB) (Burley et al., 2017) are used to produce clean ground truth.

A simulation is possible to generate datasets with statistical properties of noise close to the ones in real cryo-EM micrographs. Consequently, the composed clean-noisy pairs could be fed into the coarse CNN denoiser to produce a model that achieves roughly denoising and contrast enhancement on the cryo-EM image, for the ease of noise patch extraction.

#### 3.2.2 Patch-similarity guided noise patch extraction

If we divide a cryo-EM micrograph into patches with suitable size, these patches could be classified into two categories: patch containing specimen signal or patch of background with pure noise (shown in Figure 5). Naturally, the background patches are homogeneous to each other while the patches containing specimen signals have different patterns. Because the ice is almost transparent, the background patch represents pure noise.

Here, we proposed a patch-similarity guided algorithm to extract the noise patches in a cryo-EM micrograph:

1. Given a micrograph \(I\), denote \(I'\) with the CNN denoiser trained by the simulated data in subsection 3.2.1 to get an enhanced image \(I'\);
2. Divide \(I'\) into a set of overlapping patches \(\Theta = \{P_i\}\) (\(d \times d\) pixel\(^2\) per patch) with a step size of \(s\);
3. For each patch \(P_i \in \Theta\), further divide \(P_i\) into \(N\) local patches \(\{P_{i,j}\}\) and calculate the structural similarity (SSIM) between each \(P_{i,j}\) and \(P_{k,j}\) pairs \((k \neq k')\);
4. For the patch \(P_i\), if \(\forall k_1, k_2(k_1 \neq k_2)\), SSIM\((P_{i,k_1}, P_{i,k_2})\) is large than a given threshold \(\text{thre}\), determine \(P_i\) as a background patch;
5. Repeat 1–3 until all the background patches are identified, extract the exact patches in the original micrograph \(I\).

It should be noted that the similarity determination is operated on micrograph \(I'\) but the noise patch is extracted from the original micrograph \(I\). The similarity measurement \(SSIM(P_{i,k_1}, P_{i,k_2})\) used in our algorithm is defined as

$$SSIM(P_{i,k_1}, P_{i,k_2}) = \frac{(2\mu_{P_{i,k_1}}\mu_{P_{i,k_2}} + c_1)(2\sigma_{P_{i,k_1}}\sigma_{P_{i,k_2}} + c_2)}{\mu_{P_{i,k_1}}^2 + \mu_{P_{i,k_2}}^2 + c_1(\sigma_{P_{i,k_1}}^2 + \sigma_{P_{i,k_2}}^2 + c_2)}$$

where \(\mu_{P_{i,k_1}}\) and \(\sigma_{P_{i,k_1}}\) are the mean and standard deviation of \(P_{i,k_1}\), \(\mu_{P_{i,k_2}}\) and \(\sigma_{P_{i,k_2}}\) are the mean and standard deviation of \(P_{i,k_2}\), \(\sigma_{P_{i,k_1}}\) and \(\sigma_{P_{i,k_2}}\) are the cross-covariance between patch \(P_{i,k_1}\) and \(P_{i,k_2}\), \(c_1\) and \(c_2\) are the constants that have very small values.

#### 3.2.3 Contrast-guided noise and signal re-weighting

1. Given a micrograph \(I\), denote \(I'\) with the CNN denoiser trained by the simulated data in subsection 3.2.1 to get an enhanced image \(I'\);
Though we have designed an experimental parameters based simulation to produce simulated clean-noisy pairs (subsubsection 3.2.1), these simulated data is still not good enough to present the noise pattern in real cryo-EM images, which is more complex than the principles in the simulation. On the contrary, the GAN noise synthesizer (subsubsection 3.1.2) is able to produce noise patches with almost the same statistical properties as the real noise in the cryo-EM image. Here, we design a contrast-guided noise and signal re-weighted algorithm to transfer the noise pattern produced in the GAN noise synthesizer to the simulated clean data, to produce sophisticated clean-noisy pairs for fine CNN denoiser training. Figure 6 shows the detailed process of the re-weighted algorithm. The algorithm accepts the pure noise patches $V_i$ generated from GAN and the clean signal patches $S_i$ generated from the simulation as input, utilizing the simulated patches $X_i$ corresponding to the exact signal patches from the simulation as a reference, and outputs a re-weighted dataset $\gamma_i$ with the GAN-synthesized noise transferred to the clean simulated signal. Here we use the contrast of $X_i$ as a baseline. Denote $\gamma_i = F(\alpha \cdot S_i + \beta \cdot V_i + \gamma)$ ($F(\cdot)$ is a modulation function), the noise transfer should comply with the following objective function:

$$\min_{\alpha, \beta, \gamma} \sum_{m, n} \sum_{i} \left\| (\alpha \cdot S_i(m, n) + \beta \cdot V_i(m, n) + \gamma) - X_i(m, n) \right\|^2_2$$

where $\alpha$, $\beta$ and $\gamma$ are scalar coefficients and $d$ is the patch size. Such a minimizing problem can be easily solved by the least-square method. Then, with the solved coefficients, the signal will be re-weighted and modulated, to produce clean-noisy pairs. The constructed clean-noisy pairs are fed into a fine CNN denoiser to train the model that captures the true noise statistics and restores specimen signal from noise.

### 3.3 Implementation details

All the models are trained on two NVIDIA 2080Ti with 12GB VRAM. The GAN noise synthesizer adopts a WGAN-GP network with the weights initialized from a standard Gaussian distribution with $\sigma = 0.02$. The slope of the leak of the LeakyReLU activation for both generator and discriminator is set to 0.2. Adam optimizer is used for model training with hyper-parameters set to 0.5, weight updating $\beta_1 = 0.999$, and a learning rate of 0.0002.

The coarse CNN denoiser used for rough micrograph enhancement is trained with simulated datasets (subsubsection 3.2.1) with default initialization (Paszke et al., 2019). The fine CNN denoiser used for final denoising is trained with clean-noisy pairs generated by the GAN synthesizer and signal re-weight algorithm, initialized from the previous model weights. These two models are all trained using the Adagrad (Lydia et al., 2019) with a learning rate of 0.001. Given a trained denoiser, the denoising for a full-size micrograph is performed in overlapping patches. A padding approach is adopted to avoid the artifacts occurring at the patches’ edge.
Table 1. Three real-world datasets and four simulated datasets used for the denoisers training.

| Dataset | Electron Dose ($e^{-}/Å^2$) | Voltage(KV) | Defocus Max (nm) | Defocus Min (nm) | Pixel Size (Å) | Detector camera | Protein |
|---------|-----------------------------|-------------|------------------|------------------|---------------|----------------|---------|
| EM25    | 53                          | 300         | 2400             | 900              | 0.66          | K2             | 1ryp    |
| EM28    | 20                          | 300         | 3800             | 800              | 1.34          | Falcon II      | 2wrj    |
| EM77    | 25-35                       | 300         | 2600             | 700              | 1.16          | K2             | 5zlf    |
| SIM1    | 20                          | 300         | 3200             | 2500             | 1.34          | K2             | 2wrj    |
| SIM2    | 20                          | 300         | 3200             | 2500             | 1.34          | K2             | 1kd1    |
| SIM3    | 20                          | 300         | 3200             | 2500             | 1.34          | K2             | 1gr5    |
| SIM4    | 20                          | 300         | 3200             | 2500             | 1.34          | K2             | 1gr5    |

Table 2. Comparison of four denoisers trained with different proteins based on SSIM, PSNR (in dB) and Pearson CC. (larger is better)

| Denoiser        | SSIM  | PSNR | Pearson CC |
|-----------------|-------|------|------------|
| NT2C-2wrj       | 0.846 | 29.78| 0.823      |
| NT2C-5zlf       | 0.842 | 29.78| 0.823      |
| NT2C-1kd1       | 0.841 | 29.78| 0.821      |
| NT2C-1gr5       | 0.843 | 29.77| 0.822      |

Fig. 8: 1) Robustness of simulation-based noise pattern discovery. The first two rows show raw micrograph, ground truth and denoised micrographs of denoisers trained with datasets simulated from 2wrj.pdb, 1kd1.pdb, 5zlf.pdb and 1gr5.pdb. 2) Denoising with NT2C improves micrograph interpretability and PSNR in simulated datasets. The last two rows show comparison of different denoising methods on dataset generated with 2wrj.pdb, from left to right are Lowpass filter (2x binning), Gaussian filter, BM3D (third row), N2N-general, N2N and NT2C-coarse (last row). Detailed views of boxed region are shown at lower right corner of the micrograph.

Denoising with NT2C improves micrograph interpretability and PSNR in simulated datasets. We compared NT2C with four mainstream cryo-EM denoising methods, including three conventional methods, Lowpass filter, Gaussian filter (Haddad et al., 1991), BM3D, and a learning-based methods, N2N (Noise2Noise). Topaz-Denoise is employed for N2N where the general model provided by Topaz-Denoise is denoted as ’N2N-general’ and the Topaz-Denoise model retrained with a specific dataset is denoted as ’N2N’. We also provide a coarse CNN denoiser that is used for roughly image contrast-enhancing in the noise extraction module of NT2C, denoted as NT2C-coarse. The comparison among different methods is carried on SIM1. Here, NT2C-1kd1 is adopted for comparison. The NT2C-coarse is trained with SIM2 that is generated with protein 1kd1.pdb.

The last two rows of Figure 8 present the denoised results of Lowpass filter (2x binning), Gaussian filter, BM3D, N2N-general, N2N, and coarse-NT2C. It can be found that both N2N and NT2C remove background noise while preserving the structural features significantly better than conventional methods. The very weak particle signals in the raw micrograph are clearly restored after denoised by N2N and NT2C. The image contrast is greatly enhanced by N2N-general. However, the noise is not completely removed. Especially, as shown in the small representative area, the image denoised by NT2C-coarse contains artifacts around the specimen signal, which do not appear in NT2C. NT2C can correctly capture the true noise distribution in SIM1 and remove it from the micrograph.

We further quantitatively assessed the performance of different methods based on the SSIM, Pearson CC and PSNR (in dB). As shown in Table 3, NT2C achieves the best performance on all three assessment criteria. Especially, our method improves SSIM by 0.05, Pearson CC by 0.06 and PSNR by >3 dB over N2N-coarse which lacks true noise, and improves Pearson CC by 0.03 and PSNR by roughly 4 dB over N2N methods.

Fig. 9: Denoising with NT2C improves micrograph interpretability in real-world datasets. Comparison among different denoising methods is carried out on real-world datasets EM28. A small region is selected to illustrates that NT2C performs better in noise smoothing and signal enhancing than both conventional (Lowpass filter, Gaussian filter, BM3D) and learning-based methods (N2N).
4.2.2 Evaluation with Real Noise

To demonstrate NT2C’s ability to deal with complex latent noise in real cryo-EM images, we evaluated the performance of NT2C on three real-world datasets and compared it with Lowpass filter, Gaussian filter, BM3D, and N2N. NT2C can thoroughly remove noise and decomplex structured features from noise.

Table 3. Comparison of denoising methods based on SSIM, Pearson CC, PSNR and estimated SNR (in dB, larger is better)

| Datasets | SSIM | Pearson CC | PSNR | SNR |
|----------|------|------------|------|-----|
| Raw      | 0.40 | 0.43       | 20.87| -0.16|
| Lowpass  | 0.44 | 0.53       | 22.18| -0.04|
| Gaussian | 0.49 | 0.58       | 21.60| -0.14|
| BM3D     | 0.44 | 0.60       | 22.60| -0.07|
| TopazDe-gen | 0.67 | 0.72     | 25.36| -    |
| TopazDe  | 0.84 | 0.79       | 26.77| 0.21 |
| NT2C-coarse | 0.79 | 0.76     | 27.50| -    |
| NT2C     | 0.84 | 0.82       | 29.78| 4.88 |

This SNR has no physical meaning, just criteria for comparison. As shown in Table 3, the conventional methods only improve roughly 0.1 dB over raw micrographs. NT2C method improves SNR by 8 dB over raw micrographs and roughly 6 dB over N2N methods.

**NT2C accurately resolve complex noise model and restore clear specimen signal.** To further study the NT2C’s performance on noise removal and specimen signal restoration, we selected two representative regions from dataset EM25, one containing specimen signals and the other containing pure noise. Figure 10 presents the raw micrograph and denoised results of Lowpass filter, Gaussian filter, BM3D, N2N, and NT2C. It can be found that the pure noise region denoised by NT2C is cleaner than all other methods, where N2N removes most of the noise and the conventional methods achieve the poorest performance on noise smoothing. Moreover, as shown in the region containing specimen signal, NT2C correctly decomplex structured features from complex noise. The signal restored by NT2C presents distinct structures and the particles with different projections are easily distinguished. Table 3 gives quantitative analysis on SNR, which further proves the notable performance achieved by NT2C. It improves SNR by 4.91 dB, 4.54 dB and >4.6 dB over raw micrograph, N2N and conventional methods.

Denosing with NT2C enables more complete picking of hard-to-identify particles. We tested NT2C on micrographs with particularly difficult-to-identify particle projections, EM77, where the contrast of images is extremely low. Figure 11A shows representative micrographs before and after denoising. Before denoising, many particles were indistinguishable from noise by eye, such as the black-boxed regions a-c. After denoising, these particles in particular became readily identifiable.
Since Topaz-Denoise is the most commonly-used denoising algorithm in cryoEM, we compared NT2C with Topaz-Denoise on improving particle picking. Figure 11B shows representative micrographs denoised by NT2C and Topaz-Denoise (denoted as N2N). Figure 11E d-g shows the particles that can be clearly recognized in micrograph denoised by NT2C. However, though the images contrast is enhanced by Topaz-Denoise, these particles are still difficult to indentify from background. NT2C greatly increases protein density confidence and allows researchers to identify low-density particle views from micrographs.

In order to quantify NT2C’s improvements on particle picking, we trained three Topaz (Bepler et al., 2019) particle denoising models with about 300 particles manually picked from raw micrographs and micrographs denoised by Topaz-Denoise and NT2C, marked as raw-picker, N2N-picker and NT2C-picker. The inference of NT2C-picker generates 45300 particles, N2N-picker generates 41998 particles, while raw-picker generates 38088 particles, where NT2C achieves the improvements on the recognition rate of hard-to-identify particles by roughly 8% over Topaz-Denoise and by 19% over raw micrographs. Figure 11C-D shows the particles picked from Figure 11A-B, where the particles from raw-picker, N2N-picker and NT2C-picker are denoted by red circles, red rectangles and blue circles. A lot of hard-to-identify particles, such as black-boxed regions, are recognized after the micrograph denoised by NT2C. The excellent denoising performance of NT2C will greatly relieve the difficulty of particle picking.

5 DISCUSSION AND CONCLUSION

In this article, we proposed a denoising framework for image contrast enhancement and specimen signal restoration in cryo-EM. The key idea of NT2C is discovering the noise model of cryo-EM images over pure noise patches and transferring the statistical nature of noise into the denoiser, making the denoising based on noise’s true properties. To cope with the complex noise model in cryo-EM, we further design a contrast-guided noise and signal re-weighted algorithm to achieve clean-noisy data synthesis and data augmentation for denoiser. To our knowledge,
NT2C is the first denoising method that resolves the complex noise model in cryo-EM images. Comprehensive experiments on both simulated and real-world datasets demonstrate that NT2C is able to deal with high-level complex noise in cryo-EM images. A case study further demonstrates that NT2C can improve the recognition rate on hard-to-identify particles by 19% in the particle picking task.

Our follow work will further explore the complex relationship between image formation theory adopted in simulation and the real imaging process of cryo-EM, thus improving NT2C’s ability to restore information in real cryo-EM datasets.

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