Algorithm 1 Noise-Aliased Diffusion Steering via Reinforcement Learning (DSRL-NA) 1: **input**: pretrained diffusion policy $\pi_{dp}^{\mathcal{W}}$, offline data \mathfrak{D}_{off} and/or online environment \mathcal{M} 2: Initialize replay buffer $\mathfrak{B} \leftarrow \mathfrak{D}_{\mathrm{off}}$, \mathcal{A} -critic $Q^{\mathcal{A}}$, latent-noise critic $Q^{\mathcal{W}}$, latent-noise actor $\pi^{\mathcal{W}}$ 3: **for** t = 1, ..., T **do** Update $Q^{\mathcal{A}}$: $\min_{Q^{\mathcal{A}}} \mathbb{E}_{(\boldsymbol{s},\boldsymbol{a},r,\boldsymbol{s}')\sim\mathfrak{B},\boldsymbol{a}'\sim\pi_{\mathrm{dn}}^{\mathcal{W}}(\boldsymbol{s}',\pi^{\mathcal{W}}(\boldsymbol{s}'))} [(Q^{\mathcal{A}}(\boldsymbol{s},\boldsymbol{a})-r-\gamma\bar{Q}^{\mathcal{A}}(\boldsymbol{s}',\boldsymbol{a}'))^2]$ Update $Q^{\mathcal{W}}$: $\min_{Q^{\mathcal{W}}} \mathbb{E}_{s \sim \mathfrak{B}, \boldsymbol{w} \sim \mathcal{N}(0, I)}[(Q^{\mathcal{W}}(\boldsymbol{s}, \boldsymbol{w}) - Q^{\mathcal{A}}(\boldsymbol{s}, \pi_{\mathrm{dn}}^{\mathcal{W}}(\boldsymbol{s}, \boldsymbol{w})))^2]$ 5: 6:

5: Update
$$\pi^{w}$$
: $\max_{\pi^{w}} \mathbb{E}_{s \sim \mathfrak{B}} \left[Q^{w}(s, \pi^{w}(s)) \right]$

7:

: Opdate
$$\pi^{-1}$$
: $\max_{\pi} \mathbb{E}_{s \sim \mathfrak{B}} \left[\mathcal{Q}^{-1}(s, \pi^{-1}(s)) \right]$
: **if** access to online environment \mathcal{M} **then**

: If access to online environment
$$\mathcal{M}$$
 then

Sample latent poise action $av_{\bullet} \circ \pi^{\mathcal{W}}(s_{\bullet})$ and compute $a_{\bullet} \leftarrow \pi^{\mathcal{W}}(s_{\bullet}, u_{\bullet})$

Sample latent-noise action
$$w_t \sim \pi^{\mathcal{W}}(s_t)$$
 and compute $a_t \leftarrow \pi^{\mathcal{W}}_{\mathrm{dp}}(s_t, w_t)$

Play a_t in \mathcal{M} , observe r_t and next state s_{t+1} , and add (s_t, a_t, r_t, s_{t+1}) to \mathfrak{B}