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**Algorithm 1** Stealthing and Robust Backdoor based on Steganographic Algorithm

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**Input:** start epoch  $E_s$ , attack num  $E_a$ , end epoch  $E_e$ , client set  $C$ , selected client set  $C_m$ , adversary set  $C_{adv}$ , global model  $G$ , local model  $\theta$ , central server  $C_s$ , aggregate algorithm *PartFedAvg*, benign datasets  $\hat{D}$ , poisoned datasets  $\hat{D}_p$ , benign learning rate  $\eta_b$ , poison learning rate  $\eta_p$ , PartFedAvg gradient removal scale  $\mathcal{R}\%$

**Output:** a global model with high accuracy, stealth and defensive backdoor and high accuracy in main-task

- 1:  $C_s$  select  $n$  clients by random into  $C_m$
  - 2:  $C_s$  build a global model  $G$
  - 3:  $C_s$  send  $G$  to each client in  $C_m$
  - 4: **for** epoch  $< E_e$  and epoch  $> E_s + E_a$  **do**
  - 5:     **for** number  $k$  of client in  $C_m$  **do**
  - 6:         **if** client  $e_i \in C_{adv}$  **then**
  - 7:             Download  $G$  as local model  $L$  and train  $L$  by poisoned datasets  $\hat{D}_p$ ,
  - 8:             Compute gradient by  $\hat{D}_p$  on batch  $B_i$  of size  $\ell$
  - 9:              $g_i^p = \frac{1}{n} \sum_{i=1}^n \nabla_{\theta} \mathcal{L}(\theta_{e_i}, \hat{D}_p)$
  - 10:             **for**  $Value(g_i^p[x, y])$  in  $g_i^p$  **do**
  - 11:                 **if**  $Value(g_i^p[x, y]) \subseteq top5\%(g_i^p)$  **then**
  - 12:                     Set  $g_i^p[x, y] = 0$
  - 13:             Update  $\theta_{e_{i+1}} = \theta_{e_i} - \eta_p g_i^p$  where  $g_i^p \not\subseteq top5\%(g)$
  - 14:             Upload  $\theta_{e_{i+1}}$  to  $C_s$
  - 15:         **else if** client  $e_i \notin C_{adv}$  **then**
  - 16:             Download  $G$  as local model  $L$  and train  $L$  by private poisoned dataset
  - 17:             Compute gradient by  $\hat{D}_b$  on batch  $B_i$  of size  $\ell$
  - 18:              $g_i^b = \frac{1}{n} \sum_{i=1}^n \nabla_{\theta} \mathcal{L}(\theta_{e_i}, \hat{D}_b)$
  - 19:             Update  $\theta_{e_{i+1}} = \theta_{e_i} - \eta_b g_i^b$
  - 20:             Upload  $\theta_{e_{i+1}}$  to  $C_s$
  - 21:          $C_s$  receive  $\sum_1^k \theta_{e_{i+k}}$  and generate update gradient  $U$  for  $G$
  - 22:         **for**  $Value(U[x, y])$  in  $U$  **do**
  - 23:             Set  $g_i^p[x, y] = 0$
  - 24:         Randomly set  $\mathcal{R}\%$  of gradient  $U$  to zero
  - 25:          $G_{i+1} = G_i - U_i$
  - 26: **return** Final global model  $G$  with backdoor
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