

# MPM for Snow - Implementation Report

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## I. PARAMETERS

In general, I found that the parameters given in Stomakhin et al., 2013 to be good ones to use, despite being in 2D. I found that for the grid, a spacing of  $h = 0.05$  was best. For some reason, for  $h$  less than this, say 0.01, the snow would frequently just deflate into itself into a solid line. My suspicion is that with such a small grid size, there are less particles per grid and they may interact less (and thus slip around each other). Additionally, I found giving the snow a weight of 0.05 and a density of 100 to work best, as suggested by Nygaard et al., 2021.

## II. SEMI-IMPLICIT UPDATE

For the semi-implicit update, we need to solve the following equation (Stomakhin et al., 2013):

$$\sum_j \left( I \delta_{ij} + \beta \Delta t^2 m_i^{-1} \frac{\partial \Phi^n}{\partial \hat{\mathbf{x}}_i \partial \hat{\mathbf{x}}_j} \right) \mathbf{v}_j^{n+1} = \mathbf{v}_i^* \quad (1)$$

The main barrier to doing this is computing  $\partial \Phi^n / \partial \hat{\mathbf{x}}_i \partial \hat{\mathbf{x}}_j$ . To do this, we utilize Jiang et al., 2016 to note that,

$$\frac{\partial^2 \Phi}{\partial \hat{\mathbf{x}}_{i\alpha} \partial \hat{\mathbf{x}}_{j\tau}} = \sum_p V_p^0 \frac{\partial^2 \Psi}{\partial F_{\alpha\beta} \partial F_{\tau\sigma}} (\nabla w_{jp}^n)_\omega (\nabla w_{ip}^n)_\gamma (F_p^n)_{\omega\sigma} (F_p^n)_{\gamma\beta} \quad (2)$$

Everything in this equation is given, except for  $\frac{\partial^2 \Psi}{\partial F_{\alpha\beta} \partial F_{\tau\sigma}}$ , which we shall compute now. Following Stomakhin et al., January 18, 2013, we note that,

$$\frac{\partial^2 \Psi}{\partial \mathbf{F} \partial \mathbf{F}} : \delta \mathbf{F} = 2\mu \delta \mathbf{F} - 2\mu \delta \mathbf{R} + \lambda J \mathbf{F}^{-T} (J \mathbf{F}^{-T} : \delta \mathbf{F}) + \lambda (J - 1) \delta (J \mathbf{F}^{-T}) \quad (3)$$

The goal here is to write the RHS in the form  $X : \delta \mathbf{F}$  and we can then set  $\frac{\partial^2 \Psi}{\partial \mathbf{F} \partial \mathbf{F}} = X$ . For the first term we have,

$$\delta \mathbf{F} = \frac{\partial \mathbf{F}}{\partial \mathbf{F}} : \delta \mathbf{F} = \begin{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \end{pmatrix} & \begin{pmatrix} 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 1 \end{pmatrix} \end{pmatrix} : \delta \mathbf{F} \quad (4)$$

The second term is more complicated. Following the guidance provided in Stomakhin et al., January 18, 2013, we seek to solve the following for  $R^T \delta R$  (dropping bolds for now).

$$R^T \delta F - \delta F^T R = YS + SY, \quad Y = R^T \delta R \quad (5)$$

after which we can set  $\delta R = RY$ . First, note that  $Y$  is skew-symmetric since,

$$\begin{aligned} \delta (R^T R) &= \delta I = 0 \\ Y &= R^T \delta R = -\delta R^T R = -(R^T \delta R)^T \end{aligned}$$

Since  $Y$  is symmetric, its diagonal is zero and  $Y_{21} = -Y_{12}$ . Additionally, since  $S$  is symmetric and  $(YS + SY)^T = S^T Y^T + Y^T S^T = -SY - YS$ , we get that the equation is skew-symmetric. Thus, we only need to look at the

top-right entry of the equation to solve it. Doing so,

$$\begin{aligned} R^T \delta F &= \begin{pmatrix} R_{11} & R_{21} \\ R_{12} & R_{22} \end{pmatrix} \begin{pmatrix} \delta F_{11} & \delta F_{12} \\ \delta F_{21} & \delta F_{22} \end{pmatrix} = \begin{pmatrix} * & R_{11}\delta F_{12} + R_{21}\delta F_{22} \\ * & * \end{pmatrix} \\ \delta F^T R &= \begin{pmatrix} \delta F_{11} & \delta F_{21} \\ \delta F_{12} & \delta F_{22} \end{pmatrix} \begin{pmatrix} R_{11} & R_{12} \\ R_{21} & R_{22} \end{pmatrix} = \begin{pmatrix} * & R_{12}\delta F_{11} + R_{22}\delta F_{21} \\ * & * \end{pmatrix} \\ YS &= \begin{pmatrix} 0 & Y_{12} \\ -Y_{12} & 0 \end{pmatrix} \begin{pmatrix} S_{11} & S_{12} \\ S_{12} & S_{22} \end{pmatrix} = \begin{pmatrix} * & Y_{12}S_{22} \\ * & * \end{pmatrix} \\ SY &= \begin{pmatrix} S_{11} & S_{12} \\ S_{12} & S_{22} \end{pmatrix} \begin{pmatrix} 0 & Y_{12} \\ -Y_{12} & 0 \end{pmatrix} = \begin{pmatrix} * & S_{11}Y_{12} \\ * & * \end{pmatrix} \end{aligned}$$

Then, constructing the equation yields,

$$\begin{aligned} R_{11}\delta F_{12} + R_{21}\delta F_{22} - R_{12}\delta F_{11} - R_{22}\delta F_{21} &= (S_{11} + S_{22})Y_{12} \\ Y_{12} &= \frac{1}{\text{Tr}(S)} \begin{pmatrix} -R_{12} & R_{11} \\ -R_{22} & R_{21} \end{pmatrix} : \delta \mathbf{F} = \frac{1}{\text{Tr}(S)} X : \delta \mathbf{F} \end{aligned}$$

Finally, we get the following form for  $\delta \mathbf{R}$ ,

$$\delta \mathbf{R} = \mathbf{R} (\mathbf{R}^T \delta \mathbf{R}) = \frac{1}{\text{Tr}(\mathbf{S})} \begin{pmatrix} -R_{12}\mathbf{X} : \delta \mathbf{F} & R_{11}\mathbf{X} : \delta \mathbf{F} \\ -R_{22}\mathbf{X} : \delta \mathbf{F} & R_{21}\mathbf{X} : \delta \mathbf{F} \end{pmatrix} \quad (6)$$

Which we can rewrite as,

$$\delta \mathbf{R} = \frac{1}{\text{Tr}(S)} \begin{pmatrix} -R_{12}\mathbf{X} & R_{11}\mathbf{X} \\ -R_{22}\mathbf{X} & R_{21}\mathbf{X} \end{pmatrix} : \delta \mathbf{F} \quad (7)$$

At last, we note that  $\delta(J\mathbf{F}^{-T}) = \frac{\partial}{\partial \mathbf{F}} J\mathbf{F}^{-T} : \partial \mathbf{F}$ . We note,

$$J\mathbf{F}^{-T} = J \frac{1}{J} \begin{pmatrix} F_{22} & -F_{21} \\ -F_{12} & F_{11} \end{pmatrix} = \begin{pmatrix} F_{22} & -F_{21} \\ -F_{12} & F_{11} \end{pmatrix} \quad (8)$$

Thus,

$$\frac{\partial}{\partial \mathbf{F}} J\mathbf{F}^{-T} : \partial \mathbf{F} = \begin{pmatrix} \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix} & \begin{pmatrix} 0 & 0 \\ -1 & 0 \end{pmatrix} \\ \begin{pmatrix} 0 & -1 \\ 0 & 0 \end{pmatrix} & \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \end{pmatrix} : \delta \mathbf{F} \quad (9)$$

Putting all of this together yields,

$$\begin{aligned} \frac{\partial^2 \Psi}{\partial \mathbf{F} \partial \mathbf{F}} : \delta \mathbf{F} &= 2\mu \begin{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} & \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} \\ \begin{pmatrix} 0 & 0 \\ 1 & 0 \end{pmatrix} & \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix} \end{pmatrix} : \delta \mathbf{F} - \frac{2\mu}{\text{Tr}(\mathbf{S})} \begin{pmatrix} -R_{12}\mathbf{X} & R_{11}\mathbf{X} \\ -R_{22}\mathbf{X} & R_{21}\mathbf{X} \end{pmatrix} : \delta \mathbf{F} \\ &+ \lambda J\mathbf{F}^{-T} (J\mathbf{F}^{-T} : \delta \mathbf{F}) + \lambda(J-1) \begin{pmatrix} \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix} & \begin{pmatrix} 0 & 0 \\ -1 & 0 \end{pmatrix} \\ \begin{pmatrix} 0 & -1 \\ 0 & 0 \end{pmatrix} & \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \end{pmatrix} : \delta \mathbf{F} \\ &= \left( 2\mu \begin{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} & \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} \\ \begin{pmatrix} 0 & 0 \\ 1 & 0 \end{pmatrix} & \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix} \end{pmatrix} - \frac{2\mu}{\text{Tr}(\mathbf{S})} \begin{pmatrix} -R_{12}\mathbf{X} & R_{11}\mathbf{X} \\ -R_{22}\mathbf{X} & R_{21}\mathbf{X} \end{pmatrix} \right. \\ &\quad \left. + \lambda J \begin{pmatrix} F_{22}\mathbf{F}^{-T} & -F_{21}\mathbf{F}^{-T} \\ -F_{12}\mathbf{F}^{-T} & F_{11}\mathbf{F}^{-T} \end{pmatrix} + \lambda(J-1) \begin{pmatrix} \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix} & \begin{pmatrix} 0 & 0 \\ -1 & 0 \end{pmatrix} \\ \begin{pmatrix} 0 & -1 \\ 0 & 0 \end{pmatrix} & \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \end{pmatrix} \right) : \delta \mathbf{F} \end{aligned}$$

Thus, the derivative is,

$$\frac{\partial^2 \Psi}{\partial \mathbf{F} \partial \mathbf{F}} = \begin{pmatrix} 2\mu \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} + \frac{2\mu R_{12}}{\text{Tr}(\mathbf{S})} \mathbf{X} + \lambda F_{22} J \mathbf{F}^{-T} + \lambda(J-1) \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix} & 2\mu \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} - \frac{2\mu R_{11}}{\text{Tr}(\mathbf{S})} \mathbf{X} - \lambda F_{21} J \mathbf{F}^{-T} + \lambda(J-1) \begin{pmatrix} 0 & 0 \\ -1 & 0 \end{pmatrix} \\ 2\mu \begin{pmatrix} 0 & 0 \\ 1 & 0 \end{pmatrix} + \frac{2\mu R_{22}}{\text{Tr}(\mathbf{S})} \mathbf{X} - \lambda F_{12} J \mathbf{F}^{-T} + \lambda(J-1) \begin{pmatrix} 0 & -1 \\ 0 & 0 \end{pmatrix} & 2\mu \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix} - \frac{2\mu R_{21}}{\text{Tr}(\mathbf{S})} \mathbf{X} + \lambda F_{11} J \mathbf{F}^{-T} + \lambda(J-1) \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \end{pmatrix} \quad (10)$$

We'll write this in index notation as  $A_{ijkl}$ , where  $ij$  determine which outer matrix we are in, and  $kl$  will determine which sub-matrix we are in. Substituting this into Equation 2 yields,

$$\frac{\partial^2 \Phi}{\partial x_{i\alpha} \partial x_{j\tau}} = \sum_p V_p^0 A_{\tau\sigma\alpha\beta} (\nabla w_{jp}^n \cdot F_{p,\sigma}^n) (\nabla w_{ip}^n \cdot F_{p,\beta}^n) \quad (11)$$

Where here, using the normal conventions of index notation,  $\sigma$  and  $\beta$  are being summed over.

A note on computational efficiency: since  $\Psi$  is smooth,  $\frac{\partial \Phi^n}{\partial \mathbf{x}_i \partial \mathbf{x}_j}$  is symmetric.

### III. EFFICIENCY IMPROVEMENTS

#### III.1. Pre-Computations

The following values are utilized for multiple steps, so they are pre-computed and stored:

- $J_{E_p} = \det \mathbf{F}_{E_p}$
- $J_{P_p} = \det \mathbf{F}_{P_p}$

#### III.2. Interpolation Checks

We can reduce computational cost by not doing computations if the interpolation value  $w_{ip} = 0$ . This may seem only slightly beneficial, but the benefits are much greater with the following three observations:

**Lemma 1.** *If  $w_{ip} = 0$  then  $\nabla w_{ip} = \mathbf{0}$ .*

*Proof.* Suppose  $w_{ip} = N((x - ih)/h)N((y - jh)/h) = 0$ . Then, either  $N((x - ih)/h) = 0$  or  $N((y - jh)/h) = 0$ . Without loss of generality, let  $N((x - ih)/h) = 0$ . Then,  $\frac{N}{\partial z}((x - ih)/h) = 0$  almost everywhere. Thus,

$$\begin{aligned} \nabla w_{ip_1} &= \frac{1}{h} \underbrace{\frac{\partial N}{\partial z} \left( \frac{x - ih}{h} \right)}_{=0} N \left( \frac{y - jh}{h} \right) = 0 \\ \nabla w_{ip_2} &= \frac{1}{h} \underbrace{N \left( \frac{x - ih}{h} \right)}_{=0} \frac{\partial N}{\partial z} \left( \frac{y - jh}{h} \right) = 0 \end{aligned}$$

□

**Lemma 2.** *If  $m_i = 0$  then  $w_{ip} = 0$  for all  $p$  and  $\nabla w_{ip} = \mathbf{0}$  for all  $p$ .*

*Proof.* Suppose  $m_i = \sum_p m_p w_{ip} = 0$ . Then, since  $m_p > 0$  for all  $p$  and  $w_{ip} \geq 0$  for all  $i, p$ , we must have  $w_{ip} = 0$  for all  $p$ . The second result  $\nabla w_{ip} = \mathbf{0}$  follows from lemma 1. □

**Lemma 3.** *If  $m_i = 0$  then we can ignore all computations involving grid node  $i$ .*

*Proof.* Suppose that  $m_i = 0$  so that by Lemma 2  $w_{ip} = 0$  for all  $p$  and  $\nabla w_{ip} = \mathbf{0}$  for all  $p$ . First, note that nowhere in the (explicit integration) algorithm does a property of one grid node affect the properties of another grid node. Thus, we only have to look at when the grid is transferred back to the particles in step 7 and step 8.

- Step 1: There are no particles here so we'll set  $\mathbf{v}_i^n = \mathbf{0}$ .

- Only the grid mass is used here.
- Step 3: Here,  $\mathbf{f}_i = -\sum_p V_p \sigma_p \nabla w_{ip}$ . If  $m_i = 0$  then we can skip the sum entirely and set  $\mathbf{f}_i = \mathbf{0}$  since  $\nabla w_{ip} = \mathbf{0}$  for all  $p$ . If only  $w_{ip} = 0$ , then we can skip the matrix product summand since  $\nabla w_{ip} = \mathbf{0}$ .
- Step 4: Since  $\mathbf{v}_i = \mathbf{0}$  and  $\mathbf{f}_i = \mathbf{0}$ , we set  $\mathbf{v}^* = \mathbf{0}$  here.
- Step 5: Since we are only updating the grid velocities with collision effects, we skip the collisions for index  $i$ .
- Step 7: The computation here is  $\nabla \mathbf{v}_p^{n+1} = \sum_j \mathbf{v}_j^{n+1} \left( \nabla w_{jp}^n \right)^T$ . Since  $\nabla w_{ip} = \mathbf{0}$ , the value of  $\mathbf{v}_i^{n+1}$  has no effect.
- Step 8: The computations here are  $\sum_j \mathbf{v}_j^{n+1} w_{jp}^n$  and  $\sum_j \mathbf{v}_j^n w_{jp}^n$ . Since  $\mathbf{v}_j^{n+1}$  and  $\mathbf{v}_j^n$  are being multiplied by  $w_{ip}^n = 0$ , it doesn't matter what value they have.

□

### III.3. Grid-to-Particle Velocity Transfer

The method used by the authors to transfer the new grid velocities to the new particle velocities was (with  $N$  grid nodes):

$$\begin{aligned}
 v_p^{n+1} &= (1 - \alpha) v_{\text{PIC}_p}^{n+1} + \alpha v_{\text{FLIP}_p}^{n+1} && 4 \text{ operations} \\
 v_{\text{PIC}_p}^{n+1} &= \sum_i v_i^{n+1} w_{ip}^n && 2N - 1 \text{ operations} \\
 v_{\text{FLIP}_p}^{n+1} &= v_p^n + \sum_i (v_i^{n+1} - v_i^n) w_{ip}^n && 3N \text{ operations}
 \end{aligned}$$

Thus, the total computational cost is  $5N + 3$  operations per particle. This can be simplified as follows,

$$\begin{aligned}
 v_p^{n+1} &= (1 - \alpha) \sum_i v_i^{n+1} w_{ip}^n + \alpha v_p^n + \alpha \sum_i v_i^{n+1} w_{ip}^n - \alpha \sum_i v_i^n w_{ip}^n \\
 &= (1 - \alpha + \alpha) \sum_i v_i^{n+1} w_{ip}^n + \alpha v_p^n - \alpha \sum_i v_i^n w_{ip}^n \\
 &= \underbrace{\sum_i v_i^{n+1} w_{ip}^n}_{2N-1} + \underbrace{\alpha \left( v_p^n - \sum_i v_i^n w_{ip}^n \right)}_{\substack{2N \\ 1}} \\
 &\quad \underbrace{\hspace{10em}}_1
 \end{aligned}$$

This has a total cost of  $4N + 1$  operations per particle, a slight improvement!

## REFERENCES

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