Applications of the Ecological Visualization System Using Artificial Neural Network and Mathematical Analysis

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Abstract. This paper presents a 3D visualization system with artificial neural network algorithm that tracks the motion of particles flowing in the water, where we get a great deal of variable information, and predicts the distribution of particles according to the flowing of water and the pattern of their precipitation. Various particles and their mutual collision influencing the force such as buoyancy force, gravitational force, and the pattern of precipitation are considered in this system and we control it by normalizing momentum equation and sequential equation. Flowing particles whose motion is changed with the environment can be visualized in the system presented here as they are in real water. We can track the motion of the particles efficiently and predict the pattern of the particles as well.

1 Introduction

Technique to control the motion of the particles in the water plays important role in applications such as computer applications, utilization of water, hydrodynamics, engineering, ecology. We track the motion of particles and analyze the pattern of their precipitation to control the flowing particles in the water. To predict the result, we need various pre-processing and operation because we extract a lot of variable informations. An efficient system is necessary for exact prediction to reduce the cost and operating time during the course from collecting data to extracting information.

In the fields such as utilization of water, hydrodynamics and engineering, we are studies the resistance of water in irrigation canal, the motion of particles in the water to flood control. In recent years, in order to disposal the deposits in the water and analyze the structure of substratum ecosystem occurred by the precipitation of containment, the studies on the motion and precipitation of particles are being made most of which are only in laboratory[1,2,3,4,5]. Most of such studies need a great deal of cost and time for the reason that we have to observe and collect the data and analyze it through the simulation in artificial waterway to observe the flowing particles in the

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water and measure the pattern of precipitation[6]. The flowing particles and sediment transport are widely studied subjects. Extensive reviews of earlier works were provided by Chow [7], Vanoni [8], French [9], Chang [10], Yalin [11,12] and Nezu and Nakagawa [13], among others. Here, recent advances in numerical modeling of river hydraulics are summarized; and this is followed by a review of the recent computational modeling of sediment transport. Recent developments in related fields of particle resuspension, transport, and deposition in turbulent flow are also briefly described.

In the case of too much data with which we extract the necessary information, we do a pre-processing that reduces the dimensions with clustering technique.

Neural Network is a statistics analysis tool. It consists of a lot of components that work parallel and show the biological neural system. It is trained to operate the complex functions in various applications, such as pattern recognition, identification, classification, voice/vision control and so on. The purpose of the clustering is to set the similar samples in the same cluster. We obtain the attributes of the whole data by analyzing the cluster and apply it to decision making.

Clustering technique includes SOM, K-mean, ART and so on. K-mean clustering defines the similarity as the distance between the data in input space and minimizes the mean distance between the samples in the same cluster. It is easy to understand and realize. However, its result varies greatly according to the center of the cluster and it sensitive to the features which generate recognition error. SOM changes the weights of the neural network and performs the mapping of the data in high-dimension space into the two-dimension grid. The data that are close to each other in the input space are also close to each other in the two-dimension space. So the similarity between the data is easily visualized, and we reduce the influences of the model's initialization by adjusting the learning rate.

In this paper, in order to minimize the cost during analyzing the data and make the experiment possible in real time, we visualize the particles flowing in the water in the GUI-environment system presented here. As well, advanced and biological artificial neural network is used here to extract the motion of the particles more efficiently which have a lot of variable information.

2 System Structure

To make the experimental environment more real, we select the position, size and weight of the particles. And we can control the speed freely to create much flowing and the speed that decides the flowing. Due to the fluid energy, particles' feature, and the force between particles, there are many change in motion. We conduct the computation by inner step and visualize the result to satisfy the interaction. The visualization is more efficient than that in real environment. We denote a 3D-fluid space to analyze the particles and the direction of flowing, the depth of water and the width of water are indicated by X, Y, Z axis respectively. The particles flowing in the water have velocity V_{f_y}, which is being changed by buoyancy force(F_b) and gravitational force(F_g). The system presented here track the particles in various angles and shows the result in 3D-viewing space.

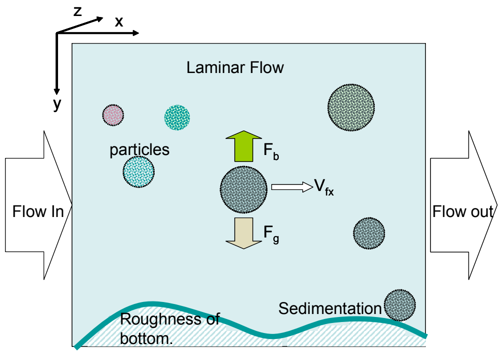


Fig. 1. The visualization model for the moving particles in water

2.1 Processing of Visualization Model

The visualization system is as follows: Fig 2. summarize the process

1. The system not only generates different weight particles, but controls the quantity of particles.
2. We can control the speed of flowing in real-time that influences the water flowing and precipitation.
3. Make the particles move in the conditions of water.
4. The particles that possess different momentum collide with each other frequently. These collisions become new parameter of particles' following.
5. We detect the particles' collisions while flowing efficiently with artificial neural network algorithm and it makes the operation fast.
6. Make the particles moving in various conditions accumulated if they get to bottom boundary condition.
7. The particles with space coordinates are visualized by the graphic library while moving.
8. Analyze the precipitation state that is changing with the motion direction and bottom structure by the visualization.

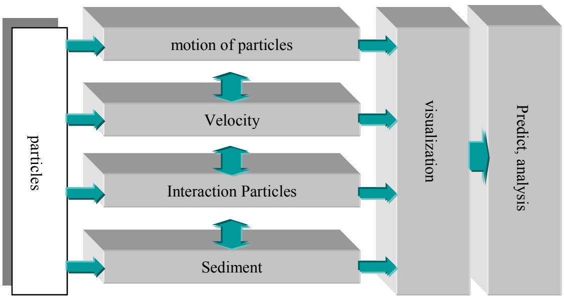


Fig. 2. Flow chart of visualization system

3 Motion of Particles

3.1 The Simulation of Fluid Velocities

The speed of fluid is very important in engineering technology. We should decide the speed of fluid to track the particles that change their loci by the flowing of fluid. We show the function of the flowing fluid by observing the motion of particles that pass the same point. In such a case, the speed of fluid is controlled by the space position and the time. On the base of the above, we normalize the momentum equation and sequential equation and search the motion of fluid [14, 15]. The flow of fluid keeps the general flow-laminar flow as shown in Fig 3, 4. In this case, the distribution of speed a parabola and the speed is regular to the time. The function of fluid speed is as following. Where , V_{fx} is velocity of fluid in XZ-plane, V_{fy} is is velocity of fluid in XY-plane

$$V_{fx} = -(y-b)^2 + V_{x_{\max}} \tag{1}$$

$$V_{fy} = K \cdot y \tag{2}$$

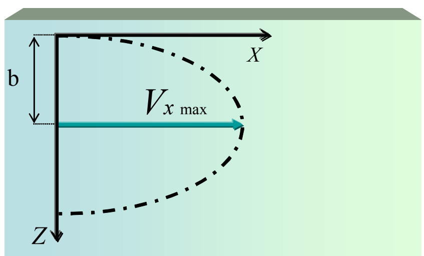


Fig. 3. Distribution of velocity in XZ-plane (V_{fx})

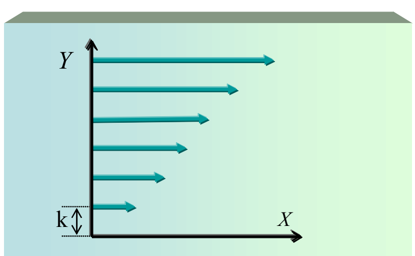


Fig. 4. Distribution of velocity in XY-plane (V_{fy})

3.2 Particle's Momentum

The momentum of the moving particles is calculated by the fluid speed. The motion of moving particles holds F_b (buoyancy force) and F_g (gravitational force), and they are decided by function (3), (4) and (5) as follows:

$$F = m \cdot a_z = F_b - F_g \tag{3}$$

$$F_b = g(\rho_p - \rho_w)v \tag{4}$$

$$F_g = \frac{1}{2} \cdot C_g \cdot A \cdot \rho_w \cdot V_{fx}^{2} \tag{5}$$

In Eq. (4), F_b is buoyancy force. Where g is acceleration of gravity, ρ_p is density of particle, ρ_w is density of fluid and v is the volume of particle. In Eq. (5), F_g is gravitational force, And C_g is a coefficient of gravitational force which is related to Reynols number, according to Hind[16], The cross section area of particle A whose value is $\frac{\pi r^2}{2}$.

3.3 Particles Interaction

The particles that move in various directions collide with each other frequently. Due to the collision, there are some changes in the particles' motion. It needs much time to track the motion and detect the collision. To predict such collision in the visual system, the system presented here uses ART2 (Adaptive Resonance Theory), which is efficient in clustering, and detects the collision changes the motion[17,18]. ART2 generates the clusters dynamically, so it isn't influenced by the number of particles.

ART2 is a self organizing clustering neural network by unsupervised learning and fast on-line learning is possible in ART neural network. It creates a new cluster dynamically or integrates new patterns with the old clusters through the vigilance test of similarity measure between a given input pattern and ART cluster. It preserves the pre-learned knowledge stably and has an ability to accommodate the new patterns. The learning algorithm of ART2 neural network are followed.

(1) Let x_k be the k th input pattern vector, and w_i be the i th exemplar cluster pattern of neural network.
(2) Given a new input pattern, a MINNET is adopted to select the winner cluster j^*, which yields the minimum distance. Generally, the Euclidean distance is used.

$$\left\| x_{k-} w_{j*} \right\| = \min \left\| x_{k-} w_{i*} \right\| \tag{6}$$

(3) The vigilance test is carried out for the input pattern. If the distance between the input pattern and the winner cluster is smaller than vigilance parameter ρ which determines the radius of a cluster, it means that the input pattern is similar to the winner cluster. The input pattern is integrated into the winner cluster and the weight of the j^* is adjusted by

$$\text{If} \left\| x_{k-} w_{j*} \right\| < \sigma$$

$$Cluster\overset{new}{j}* = \frac{x_k + w\overset{new}{j}* \left\| Cluster\overset{old}{j}* \right\|}{\left\| Cluster\overset{old}{j}* \right\| + 1} \tag{7}$$

where, $\left\| Cluster_j \right\|$ denotes the number of members in cluster j. Otherwise, a new cluster is created with the input pattern.

(4) Repeat (1) ~ (3) for all of the input patterns.

(5) If the iteration exceeds the predefined number of iteration or the cluster exemplar pattern is converged, then stop learning.

4 Particles' Sedimentation Algorithm

To make the distributed particles accumulated until getting to bottom, we change the central positions of the particles as shown in Fig. 5. (here, $m = x - 1, n = y - 1$) To decide the particles' position, we detect if the central position of particles p get to the bottom, and if other particles are accumulated under it. As well, considering the change of position due to the falling of the particles, we search the right and left side to find new position. The precipitation algorithm of system is described as follows:

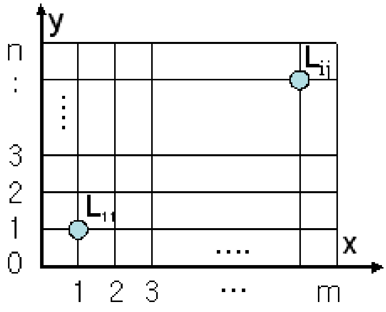


Fig. 5. Positional lattices for sedimentation ($m \times n$)

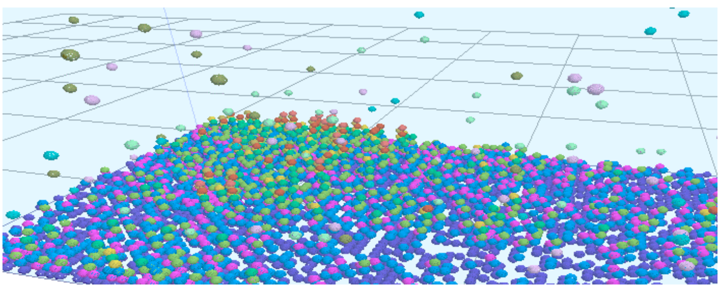
Algorithm : Sedimentation algorithm

```
Input : vertex data  P = {(x_c, y_c)}
Output :  Lattice L_ij  and  P' = {(x_c, y_c)}

All Let  L_ij = 0
for  each point (x_c, y_c) in  P  do
Let  i = ⌊x_c⌋
Let j = ⌊y_c⌋
if (L_{i,j-2} ≠ 0) then
Let  j = j - 2  and  L_ij = 1
else
call  L_ij = process  (-1,-2,*i,*j)
if  L_ij ≠ 1  then     call  L_ij = process  (1,2,*i,*j)
endif
Let (x_c, y_c) = (i, j)
endfor


Process (m_1, m_2, i, j) {
if  L_{i+m_1, j-2} ≠ 0  then
if  L_{i-m_1, j} ≠ 1  and L_{i-m_2, j} ≠ 1 then
Let  i = i - m_1  and  j = j - 2  and     L_ij = 1
else
L_ij = 0
else if  L_{i+m_2, j-2} ≠ 0  then
if  L_{i-m_1, j-2} ≠ 1  then     Let j = j - 2
else
L_ij = 0
endif
return  L_ij
}
```

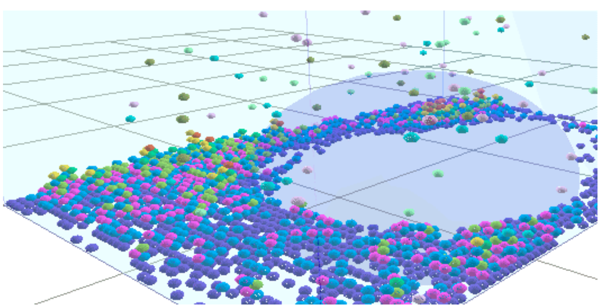
5 Results

The system presented here is implemented with Microsoft Visual C++ .Net, Silicon Graphics Library-OpenGL 1.1. We generate a 30cm□20cm□20cm cube space. In this space, the fluid flows from left to right and we generate ten thousand different weight virtual particles while the fluid speed is 10cm/s. Fig. 6(a),(b) shows the distribution of precipitation when the fluid speed is 10cm/s respectively. Fig. 6(b) shows result when substratum is added. These results make it possible to analyze the different distribution of precipitation due to the different substratum.

To analyze the distribution of the precipitated particles, we divide into five sites in direction of x-axis and twenty position in direction of z-axis as shown in Fig. 9 and table 1. We select three positions and analyze four different weight particles. The results are shown in Fig. 7. Comparing particle 1-th and particle 4-th, whose weight is the heaviest and the lightest respectively, we see the former is flowing forward but not far due to the fluid speed while the latter is flowing far away. Fig. 8. shows the result that the precipitation position varies according to the fluid speed. The particles don't move far away and sink where the fluid speed is slow, while move so far at the opposite condition.



(a)



(b)

Fig 6. The moving particles and sedimentation ((a) Without a structure of substrate, (b) With a structure substrate)

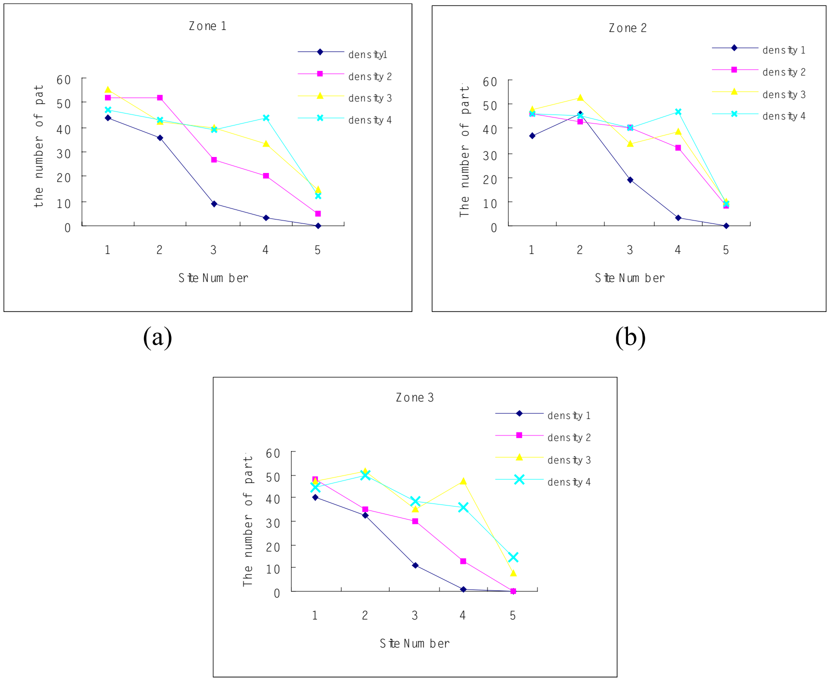


Fig. 7. The deposited particles ((a) Zone 1, (b)Zone 2, (c) Zone 3)

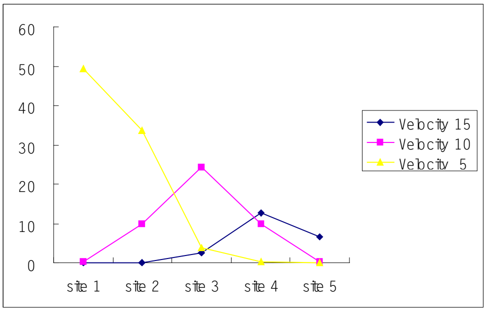


Fig. 8. Relationship between velocity and position of sedimentation

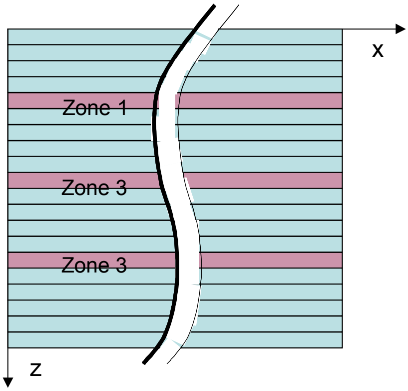


Fig. 9. Details of the Zone 1-3

Table 1. Region of site

Site number	Range of X-cord.
Site 1	$0 \le x < 7$
Site 2	$7 \le x < 14$
Site 3	$14 \le x < 21$
Site 4	$21 \le x < 28$
Site 5	$28 \le x < 30$

6 Conclusion and Future Work

This paper presented a 3D visual system using artificial neural network algorithm to visualize the motion of particles that move in the water, which possesses a lot of variable information, and to predict and analyze the distribution and precipitation of particles according to water flowing precisely. We take the force and interaction between the particles into consideration in this mathematical system so as to monitor the loci and precipitation of particles as similarly as in real conditions. Furthermore, we normalize the momentum equation and sequence equation to control as in actual condition. This system predicts not only the particles' distribution, but the precipitation pattern that varies according to the particles' features.

We need a boundary condition such as a curved line in the future work so as to predict the precipitation pattern that varies according to the structure of waterway.

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