Advanced Movement Model of Crowd Robots

Adela Béres[1,2], Károly Béres[1,3],
Mihoko Niitsuma[1,4], and Hideki Hashimoto[1,4]

[1]Integrated Intelligent Systems Japanese–Hungarian Laboratory,
Budapest University of Technology and Economics, Budapest, Hungary

[2]Faculty of Technology,
University of Novi Sad, Novi Sad, Yugoslavia

[3]Department of Telecommunication and Media Informatics, Budapest University of Technology and Economics, Budapest, Hungary

[4]Institute of Industrial Sciences,
University of Tokyo, Tokyo, Japan

`bk339@hszk.bme.hu`

Abstract — *This paper is about collision avoidance of crowd robots. For this purpose a model of potential field is proposed. This potential field, generated by a neural network, is unique to each robot. It changes in an intelligent way depending on the surroundings, basically on the space the robot disposes with. The potential field interacts with the surroundings, and calculates the next reference point the robot should move to. This paper extends with an advantageous property the research results of Mihoko Niitsuma about a movement model of crowd mobile robots in order to more efficiently avoid collisions between the robots. In her work the collision avoidance was solved with quasi Coulomb force. In her solution divergence occurred in some cases (e.g. the robot could not reach the destination point). The goal of our study is to avoid this divergence by replacing the quasi Coulomb field with a more flexible potential field solution.*

1 Introduction

In the last few years, the movement of multiple mobile robots has been studied [1, 2, 3, 4, 5]. In these studies, it is important to consider the collision avoidance, the decision of trajectory and investigate the motion behavior of the whole group. Earlier studies focused on behavior of large groups, that consisted some dozens to hundreds of robots with zero memory type. Conventional collision avoidance algorithms adopt potential methods. If the number of robots is increased, the algorithm becomes more complicated, therefore a model of crowd robots is hardly realized.

In order to deal with the realization problem of crowd robot models, a method was proposed for the collision avoidance adopting quasi Coulomb force generated among neighboring robots and between a robot and a wall. Collision avoidance is realized by generated quasi repulsion corresponding to a distance between robots. If robots move nearer to each other than a certain distance, they are required to avoid collisions. However, they do not need collision avoidance if robots are distant from each other. Therefore, it is desirable that quasi repulsion is a function that rapidly increases and decreases corresponding to the distance between the robots. Parameters to define the magnitude of the force are obtained based upon the experiences done on real human's collision avoidance. Acceleration and weight of each human are obtained by using image data of videotape recording for human's collision avoidance, and the parameters were calculated. The decision of trajectory and motion by robot's own inertia was realized as a servo system. Simulation results confirmed that the proposed collision avoidance method is able to handle a dozen robot's movements. It is found that dense and sparse state consequently occurs because of collision avoidance independent of start state of robots.

The paper is organized as follows. In Section 2 the problems of the existing model and its proposed extensions are discussed. Section 3 is devoted to describe the whole model by using the offered solutions introduced in the previous section. Some simulation results are shown in Section 4 and the last section will comprise a short conclusion.

2 The Key Elements of the Proposed Model

2.1 Advantages desired in the model

The advantage that we wanted to include in the model was the individual habit of moving of each robot, and this cannot be modeled with a radial force field. In the Coulomb model force may cause divergence, which is defined as the case when the robot swerves from the passageway or does not reach the destination, of the whole system since the infinite Coulomb force is generated between a robot and an obstacle when a robot infinitely approaches an obstacle.

2.2 Solution with arbitrary potential field

The Coulomb force field is a squarely decreasing field, therefore there are infinite heights and it never reaches zero. In order to minimize the disadvantages caused by this fact, an artificial neural network generated potential field was used. The main part of the field is the same as in the Coulomb force model, but close to a robot it reaches a maximum, and it fades quickly when it falls under a certain value. On Fig. 1 the dashed line shows the Coulomb force function, and the full line shows the neural network generated field. Although there is still one possibility for divergence. In order to avoid this divergence, the system changes some parameters in certain circumstances. Divergence could occur if too many robots are in the path and the repulsion is too high, thus the current robot cannot pass between them. In these situations the change of its potential field is required. These fields belong to a certain behavior pattern. In the advanced model each robot has a personal way of moving. They differ from each other in the implanted speed, as well. The parameters of behavior need to change dynamically, in order to avoid divergence. In the previous well-constructed model the movement and decision of trajectory was modeled with Coulomb force, and showed adequate results, so the field of other robots is modeled in the same way, the exact robot currently in sight uses a special force field generated by a

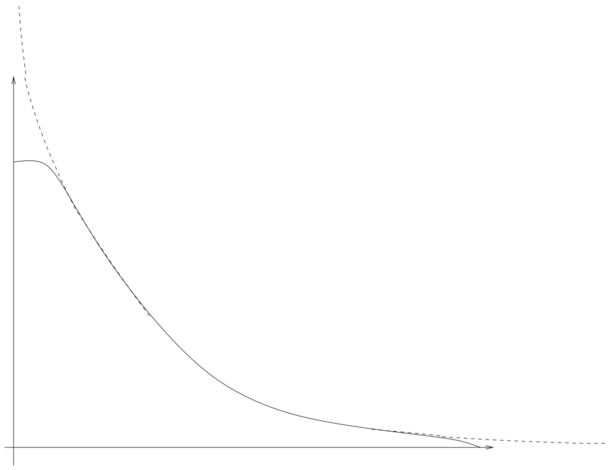

Figure 1: The potential field generated by the Coulomb force function and by the artificial neural network

neural network. It has indentations and swells depending on the structure of the individual robot.

2.3 The Potential Field

In intelligent systems, it is usual to take an example from real world. If a person has a broken hand or a high value bag in his hand he will evade everything approaching that part even if it needs to get closer to something else on the other side. Or if an individual has a practice to generally keep his right side as far as possible from the others, he will feel uncomfortable if someone approaches him from that particular side. Therefore the model distinguishes e.g. a robot which holds a delicate object, from a robot which can be dangerous to its environment. Each robot sees the other robots as equal potential obstacles, with a fixed potential field. The force that attracts the robot toward its destination has a constant value, which means it makes no difference if the robot is far or close to the target.

Every robot has a unique potential field, as mentioned before, so in one and the same situation the robots may act differently. Each target is modeled with a positive charge, which attracts the robot with the same intensity in every location of the used space. The target is represented by a constant intensity, normalized force pointing towards it. That means, the robot will not go faster towards the target even if it is close to it. According to this, the target is an object pulling the robots towards him, with an invariable force intensity. Its effect on the robots is positive, and of course it affects only the robots that are chosen to reach that particular target. The potential fields of the robots are modeled with a negative charge, so they are pushing each other, and basically they have the same shape, a Coulomb field. But because a unique potential field was desired, modifications were made on each robot. The modifications were made by putting various positive parts into the original negative field, which could be modeled in electrostatics as an inhomogeneous charge. Walls are modelled as the field of a negative plane charge. The resultant force that appeals towards the target is the sum of two vectors, the target vector and the repulsion vector that occurs between the robots or between a robot and a wall. Shown later on

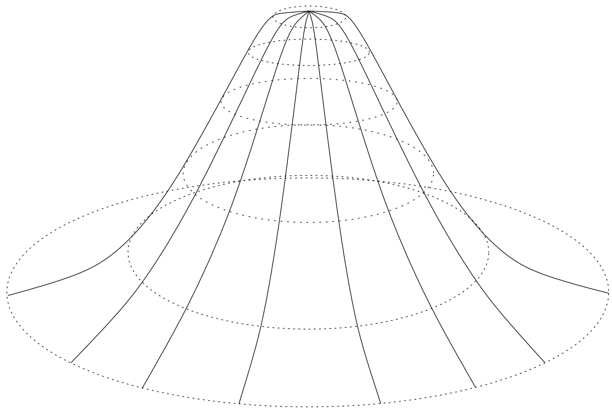

Figure 2: An example for the potential field

figures of simulation Fig. 7.

$$F_{res} = F_{tar} + F_{push}$$

The total field in application is realized as an approximation of a set of functions applied to distance measuring sensors mounted radially around the robot. The functions, each of them generated by a neural network, use the data from the sensors, distance and density, as their input and produce output for the “brain”, the trajectory decision neural network. A possible field, a set of functions, is shown on Fig. 2.

2.4 Decision Method of Trajectory

Because collision avoidance is unpredictable and also not deterministic, a movement of a robot has to be sequentially corrected. The trajectory of the robot’s movement is a sequence of reference points. The reference point is an arbitrary point on the line segment connecting the current position of the robot and the destination. Its norm changes due to the value of repulsion, but only slightly, since the force field of repulsion is normalized. The trajectory is produced to choose the optimal path for the robot, e.g. the way as safe as needed for current robot.

The trajectory also changes the potential field of the robot. If the robot had to change its direction from the last move, the potential field is sharpened, and if it could continue as planned, the potential field is softened.

2.5 Sharpening and Softening

Generally, humans behave differently in crowded and less crowded environments. For example, a person can feel very uncomfortable if somebody approaches him directly on a small density street, but the same man will accept the fact that in a crowded bus he cannot avoid other people’s closeness. So the will of by-passing other people depends on the density of people in that particular area. The robot model responses similar to the density problem. Pushing parameters are modified every time, when a robot meets another robot or a wall. In these cases the robot must change its course, and therefore its potential field changes, too. At first, the robot’s potential field has high values, so it wants to avoid meeting with other robots in the largest circle of its potential field—which is unique. After

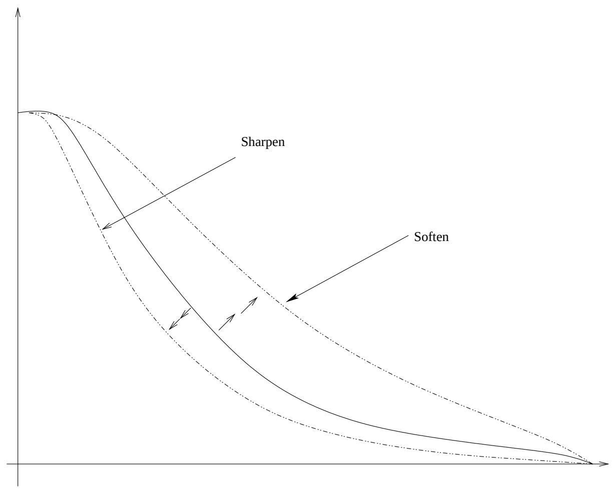

Figure 3: The effect of the sharpen and soften on the potential field

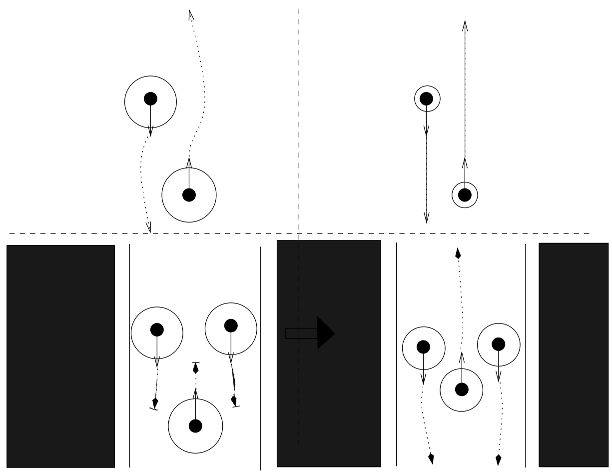

Figure 4: Sample movements in the original way and by using the sharpen and soften

every meeting with another robot, a sharpening is done on the potential field (see Fig. 3). If there is a large number of robots on the location, many sharpening will be made so the repulsive force between robots will become smaller and smaller. On the other hand, if for some time meeting did not occur, than a softening is done. This sharpening and softening produces a minor change, considered as an offset to the sharpening and softening caused by values coming from density measurement. Some possible ways of movements are shown in Fig. 4.

3 The Model

The “brain” is realized as an artificial neural network with three sets of inputs (Fig. 5) These inputs generate the coordinates of the resulting force. The first input is the force that points towards the target. After every evasion it must be recalculated. As already mentioned, the intensity of this force is constant and positively affects the robot. The second input gives the resultant negative push force, which is the sum of every force, that

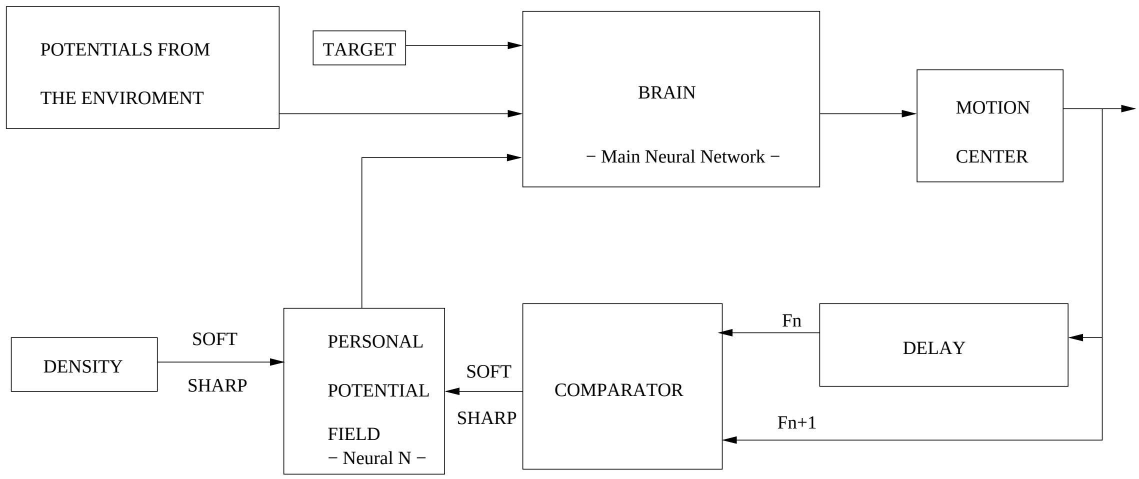

Figure 5: Block scheme of the movement model

was generated by other objects. These objects can be either other robots or obstacles. The third input is the output of the potential field of the observed object; which is also realized as an artificial neural network. Although its characteristics remain the same and unique, the value of the result is higher or lower according to the modifications of the network's two inputs. At first, the population density is measured in a large space of the particular, and its value gives the starting maximum radius of the potential field. During the robot's motion it is also recalculated repeatedly. If a difference in the density is detected, sharpening or softening is needed. On the other hand, every direction change of the resultant force, produces sharpening or softening. It is detected by a comparator, which compares the current value and the previous value of the resultant force. The output of the brain is directly connected to the motion center. The motion center is realized as a servo system, which was discussed in an earlier work [6].

4 Simulation

A simulation was made, where in every step the exact robot uses the arbitrary potential field for itself, and calculates with the modified radial quasi Coulomb force like field for the others. Simulations were made for some dozens of robots, and the only failure in reaching the target happened, when the robots physically could not fit into the corridor. Two steps of the simulation are shown on Fig. 6 and Fig. 7 with forces attracting the robot.

A robot was also built holding distance measuring sensors and an image processing system for density measurement, but it needs some more development, hence problems with dead time of the sensors.

5 Discussion and Conclusion

The model discussed in this paper changes the model of potential field of the existing model, to one determined by a fuzzy-neural system, so it became much more flexible, almost any kind of robot behavior can be modeled with the help of this. Simulations and testing have been done.

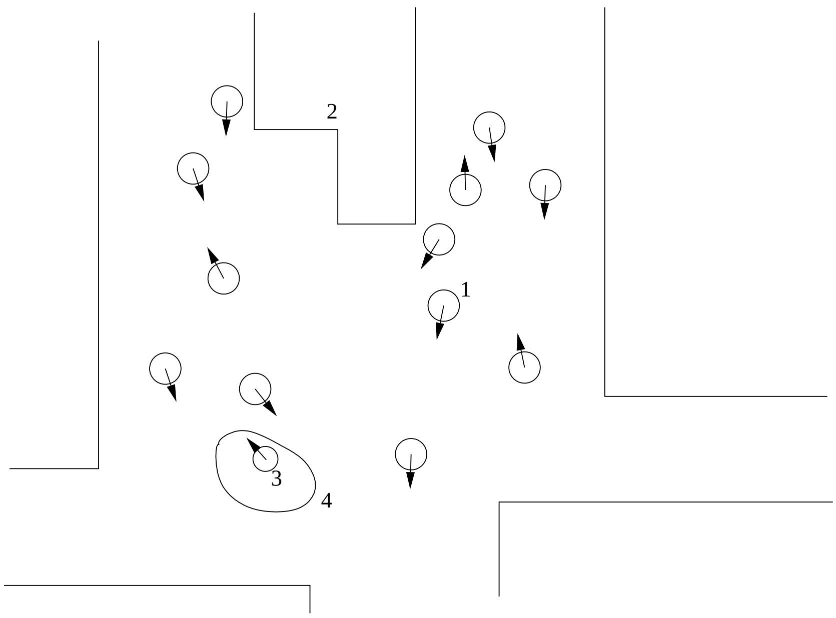

Figure 6: Simulation results of the robots in a crowded environment

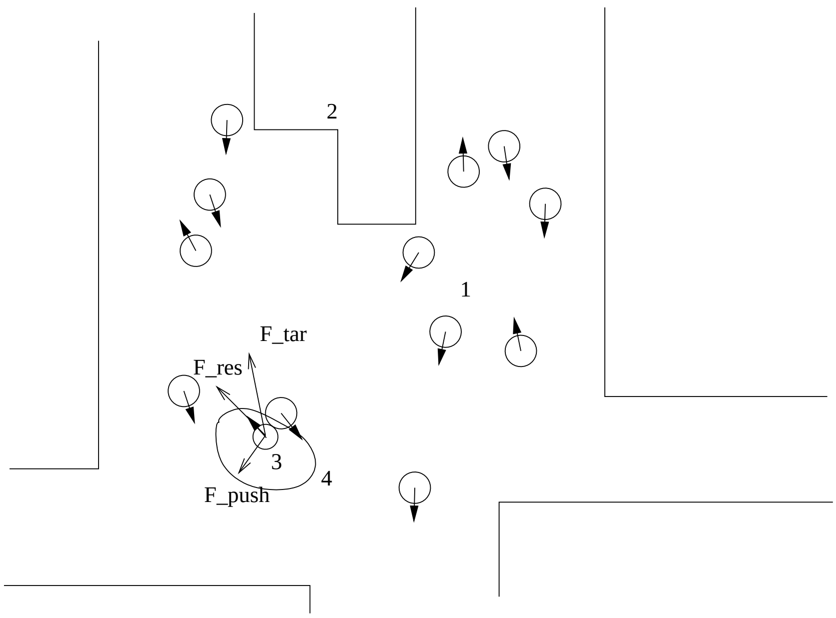

Figure 7: Simulation results indicating the forces attracting the robot

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