Multiple and weighted Potential Fields in arena games

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Abstract

Potential Fields is an obstacle avoidance and general path-finding technique that has only quite recently started to be used in AI for video games. It has previously mainly been used in robotics for robot navigation.

Although quite unexplored, Potential Fields have so far worked well in video games. Previous research has mainly focused on RTS (Real-Time Strategy) games. This research explores the use of Potential Fields in another genre called arena games (which is a quite unexplored genre as well).

In the implementation, multiple Potential Fields have been used together, where each field had a different task. Also, weights were used on the different Potential Fields to give them different importance depending on some factors that are dynamic through the game, hence the use of the word weighted. The main focus of the user studies conducted was the impact the weights had on the computer controlled unit’s general behaviour.

The user studies conducted showed that it was hard to determine who was a computer controlled character and who was human controlled, therefore telling that multiple Potential Fields worked well for movement. The test participants became better at determining this the second match they played, no matter the properties of the match.

However, the user studies did not show that the weights made a remarkable difference; there was no significant improvement on the situation adaptation and team cooperation, but no deterioration either. The concept of using weights needs to be explored further.
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1 Introduction

When playing multiplayer games, one can sometimes find oneself in lack of other human players. In physical board games this is not as easily solved, but in the video game industry, computer controlled players have spread far and wide to fill these gaps.

Naturally, many different techniques have developed to satisfy the many different needs for behaviour from a computer controlled player, where world movement is one big part of almost any game genre.

When developing the game Formless, we (as in the development team) always knew that the game could not be played without other human players. That's when the thought of developing an AI for the game occurred to us.

We knew that the major issue of the AI behaviour for our game would be world movement, and thus recalled hearing about Potential Fields and how they could be used. Potential Fields had not been used in the game genre, and so we decided that we wanted to research further how well they would fit this game.

1.1 Background

Potential Fields is a quite unexplored area of video game AI, and is one of Blekinge Institute of Technology’s research areas. It has mainly been researched for its use in Real-Time Strategy games, although this does not restrict it to this genre. It mainly fits as a form of path finding, but has other uses.

A computer controlled player needs to adapt to different situations that occur in the battlefield; attack when enemies come close and defend and heal the team when the health level is low. This means that being close to opponents or team mates can be of different importance depending on the health level in the team, number of players in range and other factors.

To meet these demands in the implementation, multiple Potential Fields will be used, where one field may pull the AI towards a good shooting distance to opponents, while another pushes the AI away from impassable parts of the map. Depending on the battle situation, the different fields’ impact on the final movement result can be varied with weights. As an example, a field that promotes healing team mates may have greater importance and a higher weight when a team mate is low on health.
The goal is to implement an AI team mate that can be used in the game Formless in the future. There are also several purposes for the thesis: for the author to investigate an interesting area of AI, to add to the content and attractiveness of the game Formless, and to explore how Potential Fields can be used in a new game genre.

1.2 Research questions

• To what extent can Potential Fields be used for AI calculations in a fast-paced, multiplayer arena-based game?
• What is the impact of using dynamic weights on Potential Fields, when multiple fields are used together?

1.3 Hypotheses

• Potential Fields can be used as the only way of movement for the AI, and still make it appear to consider several different aspects at once.
• Dynamic weights balances the different Potential Fields, making the AI cooperate better with its team.

The first hypothesis will be answered with the final solution of the implementation: was it possible to do? The second hypothesis will be answered by survey results after a test (see more information about the test and survey in “Methodology”).

1.4 Target audience

Anyone who is interested in the use of Potential Fields for game AI, or AI for fast-paced multiplayer and/or arena games in general, would be interested in this research.

1.5 Delimitation

Our main focus is on the use of Potential Fields, and the Potential Fields will be implemented for a single game (the arena game Formless).
1.6 Methodology

The following steps will be taken:

1. Implement an AI that uses multiple potential fields to move around, where the weighting of a field can be turned on and off.

2. Conduct a user study where players get to bring a computer controlled character and play with it in multiplayer battles. Participants will test both static potential fields, and the solution with dynamic weights. One test session will contain:
   1. A standard battle of 4 minutes without AI’s, where 4 people play against each other in two teams.
   2. A battle of 4 minutes with AI’s, where 4 people play against each other in two teams. All players bring an AI unit each that uses static potential fields.
   3. A battle of 4 minutes with AI’s, where 4 people play against each other in two teams. All players bring an AI unit each. The Potential Fields of this unit are altered dynamically by weights during the game.

   The order of the two last battles is switched for half of the participants.

3. Evaluate the overall player impression of a weighted solution with surveys. The results of the tests of the different users will determine if the adaptivity made any difference.

During this test, both of the presented hypotheses will be tested.

The first hypothesis tells that Potential Fields can be used as the only way of movement for the AI. If, at the moment of testing, there is no other way that the AI makes its movement decisions than Potential Fields, then the hypothesis was correct.

The second hypothesis tells that dynamic weights on the different Potential Fields will make the AI more adaptive and cooperate more. The survey to be filled in by the testers will contain questions asking about the tester’s experience of the games played, with and without the dynamic weights. This will determine the correctness of the hypothesis.
2 Arena games and Formless

Although we call “arena games” a video game genre, it is not officially a video game genre. In the development process of the game Formless, no other genre fitted, so “arena” or “arena based” is what was used. Therefore, in describing the genre, only the basic game play concepts of Formless are used as reference.

2.1 Arena games

The main purpose of an arena game is to bring players together in a multiplayer game that takes little time to understand, and quickly gets action started.

Each player has a number of choices to make that affects different properties, as maximum health, speed or what (and/or how many) abilities that are available. These choices make the game more strategic, and gives the game variety.

When these choices are made, players are thrown into an arena (a limited area) and try to hit each other with the previously mentioned abilities. There can be different game modes, where scoring the highest number of kills or surviving the longest are examples of that.

The simplicity of the game is its strength: anyone can easily play and have fun, and it lasts as long as the player wants to.

2.2 The game of choice – Formless

A game AI will be implemented for an arena game called Formless.

Formless is school project game, made by seven students at the program Game Programming at Blekinge Institute of Technology November 2010 – March 2011, where the thesis author is one of these seven students.

In this game, your choice of abilities to bring is mostly free. In the current version of Formless (BETA version from April 2011) there is one game mode. You play the game in two teams, preferably teams of 3 or 4. You have 4 minutes to score more kills than the opposing team, and when killed you are continuously resurrected (brought back to life). Most of the abilities are ranged attacks. You can also equip traits, which are modifications to your common attributes, instead of some abilities.
It is fast to get going, but it lasts as long as you have enough people to play with.

This is where this thesis comes in, “as long as you have enough people to play with”. The idea of developing an AI for this game, was to fill any possible gaps in the teams, when not eight people are available. The goal of the AI is to make the player feel that the AI extends him or her, as a tool or aid, and the player should not have to think about what the AI does. It should feel like a team player, but if the AI is too good at playing the game, there is an advantage in taking an AI companion instead of a fellow human player, which is not the goal. As a player, you should like to bring your AI companion, but you should prefer playing the game with only other human players.

The full concept document of the game, with graphics style, some abilities, story etc. can be found in Appendix A – Formless BETA concept document.

3 AI and Potential Fields

An AI using Potential Fields will be implemented for an arena game. Although, some clarifications are first needed on the concepts of the expressions we just used: AI, potential fields and their relation to games. We have already described the term arena game, and the specific game of choice.

AI, or artificial intelligence, is used for many different purposes in many different situations today. According to Russel and Norvig in Artificial Intelligence, A Modern Approach, artificial intelligence is the creation of computer programs that either “think humanly”, “think rationally”, “act humanly” or “act rationally”, or any combination of these four aspects. Russel and Norvig also mention some of the uses of AI, bringing up examples such as robotics, speech recognition, game playing, machine translation and logistics planning [Russel 2010].

We have chosen to branch ourselves in two ways in the area of AI. Firstly, we have chosen the use of AI in computer games rather than anything else computer related. Secondly, we have chosen the use of Potential Fields, a game AI branch that is most commonly used for Real-Time Strategy games (which is not the genre of the game in focus here).
3.1 Game AI

According to Brian Schwab in *AI Game Engine Programming*, such a broad description as Russel and Norvig’s is not required for game AI in particular. Game AI is all about appearance of intelligence, and behaviours that are relevant, effective and useful in the presented situation (with emphasis on appearance) [Schwab 2009].

Game AI has developed a lot, from game characters acting in quite predictable patterns, or “cheating” on the player by having much more information than the player could possibly have, to much more realistic opponents that seem to be able to think rationally, plan ahead and learn from mistakes. This development is mainly due to computer hardware development: A faster CPU can perform more calculations and therefore simulate more complex behaviours [Schwab 2009].

The first game genre to actually put focus on AI was strategy games, as graphics alone do not make a good, or even playable, strategy game, according to Paul Touzor in *AI Game Programming Wisdom*. A strategy game AI needs to perform path finding for hundreds of units, while as well needing to make more overall tactical and strategic decisions [Rabin et. al. 2002].

Although Touzor claims, as Schwab, that hardware constraints have been a major reason for the roadblock of game AI, he also suggests that “AI has been a last-minute rush job” and that AI now develops as a result of game developers taking AI more seriously [Rabin et. al. 2002].

One important thing to note in game AI, is that the player of the game is looking for some kind of satisfactory feeling of achievement. AIs that lose all the time or win all the time are easy to develop, but not fun to play against, or with. Bob Scott discusses this in *AI Game Programming Wisdom*. An AI needs to be believable in it is behaviour; intelligent target selection is expected, while inhuman accuracy is not [Rabin et. al. 2002].

3.2 Artificial Potential Fields

Artificial Potential Fields (hereafter called only Potential Fields) is a relatively new approach to AI. It has originated from robotics, and was first introduced in the 1980’s as a solution to obstacle avoidance for mobile robots. It continued to mostly be used for obstacle avoidance when brought into the world of video games in the early 2000’s. In some of the theses on the subject by Johan Hagelbäck and Stefan Johansson found in *A Multi-Agent Potential Field Based Approach For Real-Time Strategy Game Bots*, they thoroughly describe how they have used Potential Fields in Real-Time Strategy (RTS) games, and
these are some of the most in depth explorations of the use of Potential Fields in video games to be found today [Hagelbäck 2009].

3.2.1 How do they work? ¹

The basic idea of Potential Fields is to put a charge at an interesting position in the game world and let the charge generate a field that gradually fades to zero. The charge can be attracting (positive) or repelling (negative). When choosing which way to go for a unit of some sort, the direction with the highest charge is chosen, and in this way, the unit moves towards an interesting point in the world.

In the following pictures, the green dot is our unit that we want to find a path for, the point E is the goal point we want to reach and brown tiles are impassable tiles. Light blue tiles are attracting tiles and black tiles are neutral.

When our unit now is to choose which tile to walk to in Figure 3.1, it chooses the most attracting tile, and will walk towards the goal point. However, there is a small risk that the unit bumps into the impassable tiles.

¹ All information in Section 3.2.1 and Section 3.2.2 was collected from http://aigamedev.com/open/tutorials/potential-fields/ at 15 April 2011.

The original text is written by Johan Hagelbäck, and all pictures belong to him. Some parts of the describing text are quotes, other are modifications to Hagelbäcks original. All information is used with his approval.

Figure 3.1: The goal point E generates a positive charge, that gradually fades to zero.
We have in Figure 3.2 added some slightly repelling fields around the impassable tiles, as a method of obstacle avoidance. The unit will now rather choose a path around the impassable tiles, than a path close to them.

![Figure 3.2: The impassable tiles have generated slightly repelling fields.](image)

Even though finding a good path to a goal destination is a good thing, it is seldom the only part of moving around in a game world. What is more important in arena games to win, is to find enemies and attack them. To be able to attack, a good distance is key. What is meant by a “good distance”, is determined by the range of the attack we want to use.

In the implementation, the principle of Figure 3.3 is used. When we can reach the enemy unit with our attack, we have a highly attractive field, but closer than that is not desirable.

![Figure 3.3: The most attracting fields are at the best shooting distance to the red enemy unit.](image)
3.2.2 Local optima problem and pheromone trails

One of the most common issues with potential fields is the local optima problem.

Figure 3.4 shows an example where this problem arises. The destination E generates a circular field that is blocked by impassable tiles. The unit (green) move to positions with higher potentials, but end up in a position (as shown in the figure) where the highest potential is where the unit currently stands. The unit hence get stuck.

A solution to this problem is called pheromone trail. The name origins from natural ant behaviour. When ants walk, they leave a pheromone trail on the ground for other ants to follow (e.g. when the trail leads to some food). Although among ants this trail serves as a guide for which way to go, in the Potential Field case the trail is used to push a unit out of a local optima problem and keep it moving, preventing it from standing still and/or getting stuck.

Basically, the most recent positions of the unit, including the current, are saved, and those positions generate slightly repellent potential values. This makes unvisited fields more attracting than the ones we just visited, and we create a movement. Pheromone trails will be used in this implementation.
4 Implementation

In the implementation multiple potential fields are used together. Most of the potential values are calculated by functions, square equations in particular. A square equation generally looks like this

\[ y = ax^2 + bx + c \]

where \( a, b \) and \( c \) are constants. In this particular situation, \( y \) is the potential value and \( x \) is the distance (to the AI, to a wall etc.).

There are four different fields used: Static field, attack field, healing field and trail field.

The fields used are two-dimensional arrays, with \((0, 0)\) being the upper left corner, \((450, 450)\) the middle point and \((900, 900)\) the bottom right corner.

The game world (the arena) in Formless is circular, with an impassable area in the middle of the arena. The whole arena in its entirety has a diameter of 900 units, with \((0, 0)\) being in the middle of the arena, \((-450, 0)\) being the leftmost point and \((0, -450)\) being the bottom point. Although the world is in three dimensions, movement only occurs in two.

Figure 4.1: How the coordinates in the field (left) and world (right) are built up
This means that the y axis is different in the two coordinate systems (explained further by Figure 4.1 above). Therefore all world positions had to be transformed into coordinates in the array with

\[
x = x + 450 \\
y = (-y) + 450
\]

And array coordinates could be transformed into world coordinates with

\[
x = x - 450 \\
y = (-y) + 450
\]

When deciding where to go, the AI collects data from all its potential fields. It collects data in 8 different directions: up, up-right, right, right-down, down, down-left, left, left-up. The ninth position used is the position the AI is currently standing on, meaning standing still. The data is collected 10 units away from the AI’s current position, since the size of a player is 10 units.

```
for all fields do
    tempValue[0] = field.calcPotential(myPosition.x, myPosition.y + 10)
    tempValue[1] = field.calcPotential(myPosition.x, myPosition.y - 10)
    ...
    for 9 positions do
        value[index] += tempValue[index]
    end for
end for

for all values do
    if values[index] > values[highest] then
        highest = index
    end if
end for

if highest is upwards then
    walk upwards
else if highest is downwards then
    walk downwards
end if
```

Figure 4.2: Making the decision where to go

The result value of a field calculation is always added to the other field’s values, although the field internally may work differently (more information about this in Section 4.5).
4.1 Static field

The static field takes care of general movements in the world. Being close to the impassable area in the middle, or being close to the edges, is bad, so a square equation was constructed with its maximum point at a distance of 300 units to the middle.

The equation used:

\[ y = -0.005x^2 + 3x - 450 \]

This gives us a potential value \(-200 \leq y \leq 0\), where being further away or closer than 300 units from the middle point generates a negative value. Thus, the static field only generates repelling potential values.

All values are pre-generated at the creation of the field, and can be fetched at any time.

**Figure 4.3: The static field function graph**

\[
\text{Figure 4.4: Creation of the static field}
\]

```plaintext
for all x, y in field do
    distance = distance between (x,y) and the middle
    field[x][y] = -0.005 * distance^2 + 3 * distance - 450
    if field[x][y] > 0 then
        field[x][y] = 0
    end if
end for
```

**Figure 4.5: The calcPotential function for the static field**

```plaintext
StaticField::calcPotential(x, y)
    transformedX, transformedY = transform(x,y)
    return field[transformedX][transformedY]
end function
```
4.2 Healing field

The healing field makes sure that the AI keeps a good shooting distance to team mates, as the healing ability used is a ranged ability. In this case a distance of 150 units is used, which is the range of the healing ability.

The equation used:

\[ y = -0.005x^2 + 1.5x \]

This gives us a potential value \( 0 \leq y \leq 110 \), where being at a distance of 150 is the best, and the value fades to zero the closer or further away we get.

In both the healing field and the attack field, weights are used depending on the opponents' current health status.

When calculating the weight, the thought was the following:

\[ \frac{\text{currentHealth}}{\text{maxHealth}} \]

This gives us a value between 0 and 1, which indicates how much health we’ve got left, where 1 is full health and 0 is being dead. 1 - this weight gives us how much health we’re missing.

The more health we’re missing, the higher potential value we want. If we have full health, the result will be 1 - 1, giving us 0, meaning that the player is not interesting at all and will not generate any attracting values. If we’re low on health we get, as an example, 1 - 0.1 which is 0.9. The highest value generated by this player is then the result of the equation * 0.9.
Figure 4.7: The calcPotential function for the healing field

```
HealingField::calcPotential(x, y)
    returnValue = 0

    for all team mates do
        weight = 1 - (teammate.currentHealth / teammate.maxHealth)
        distance = distance between (x,y) and teammate's position
        potentialValue = -0.005 * distance^2 + 1.5 * distance
        if weights are activated then
            potentialValue = potentialValue * weight
        end if

        if returnValue < potentialValue then
            returnValue = potentialValue
        end if
    end for

    return returnValue
end function
```

Starting with setting returnValue to 0, makes sure that no negative value is ever returned, and thus the healing field only generates attracting values. Also, note that only world positions are used, and no transformation is necessary.
4.3 Attack field

The attack field has the same basic idea as the healing field: a good shooting distance to opponents of low health. It has the same range as the healing ability, and therefore the same equation was used.

The weight used works almost the same as the healing field weight, except from the fact that the base value 1 is switch for a base value of 1.5. This is caused by the fact that a team mate with full health is not interesting at all, while an opponent with full health still is interesting.

If we have full health (1) we want the potential function to slightly affect the return value, and to achieve that the base value needs to be greater than 1. With the base value 1.5 we get 1.5 - 1 = 0.5 when the health is full, and if we’re low on health we want the return value to be higher than it would be for a team mate, 1.5 - 0 = 1.5.

```
AttackField::calcPotential(x, y)
    returnValue = 0
    for all opponents do
        weight = 1.5 - (opponent.currentHealth / opponent.maxHealth)
        distance = distance between (x,y) and opponent's position
        potentialValue = -0.005 * distance^2 + 1.5 * distance
        if weights are activated then
            potentialValue = potentialValue * weight
        end if
        if returnValue < potentialValue then
            returnValue = potentialValue
        end if
    end for
    return returnValue
end function
```

*Figure 4.8: The calcPotential function for the attack field.*

Just as with the healing field, the attack field only generates *attracting* potential values, and no position transformation is necessary.
4.4 Trail field

The trail field works quite different from the other fields. It is based on the pheromone trail technique described in Section 3.2.2. It is continuously updated with the previous 100 positions of the AI, saves them, and puts repelling values on these positions, with the most current position generating the strongest repellent, and the oldest position being set back to 0.

In the following pseudo code in Figure 4.9, the first for-loop moves all trail positions backwards in the array. It starts with the last trail position becoming the previous trail position and then decrements index and continues to push the content back. During the last loop execution, trail[1] will get the position of trail[0], then holding the previous AI position. After that, the current AI position is put on trail[0]. This way the most current position is always at trail[0], and the further back in the array we look, the older positions we find.

The second for-loop gives the field potential values on the positions saved in trail, giving trail[0] the most negative value and fading it to zero as we progress through the trail.

```
TrailField::update(AIposition)
  for trail size - 1 do //index decrementing
    trail[index] = trail[index - 1]
  end for
  trail[0] = transform(AIposition)

  potentialValue = (trail size - 1) * -2
  for trail size do
    field[ trail[index].x ][ trail[index].y ] = potentialValue
    potentialValue = potentialValue + 2
  end for
end function
```

*Figure 4.9: Updating the trail field*

```
TrailField::calcPotential(x, y)
  transformedX, transformedY = transform(x,y)
  return field[transformedX][transformedY]
end function
```

*Figure 4.10: The calcPotential function for the trail field*
4.5 Combined fields

Figure 4.11: An overview of the result of the combined fields

Figure 4.11 shows a simplified view of the effect of all the combined fields (e.g. the attack and healing fields do not generate as strong values as the static one).

Firstly, on the edges we see the repelling values of the static field.

The circles around the players show the effects of the attack field and healing field. The team mate with full health has the weight 0 and therefore generates nothing, while the team mate with low health generates quite strong attracting values. The opponent with full health generates slight attracting values, while the opponent with low health generates the strongest attracting values.

The picture shows the state in one update frame: In the next update frame, the health levels may have changed and the values altered.

Note that the values on two different players in the same team do not add up, while the values for a player and for the static field and values on two different players in different teams do. The two different teams are in two different fields, and all different fields are always added up, while the healing field and attack field internally only picks the highest value.
Lastly, the trail is shown behind the AI, showing where it has previously been. The position behind the AI generates the strongest repelling value, and the older the position, the weaker the value.

4.6 Why square equations?

In most of the implementation, an active choice has been made to mainly use square equations, which needs motivation. Instead of using a square equation that looks something like this

![Square equation graph](image)

a linear equation with a maximum could be used, looking something like this

![Linear equation graph](image)

but in all cases, we chose the square equation. This is due to the fact that there is no single extreme point where it's best for the AI to be and where all positions from there get linearly worse. In the static field, we only need to keep away from the edges, being in the exact middle between the outer edge and the middle impassable area is not important and not even interesting.

Quite the same can be said about the healing and attack field. There is a small area where an AI can reach an opponent or team mate where we want it to be, but it's not really strict that the AI is standing at the exact range of attack/heal.

The static field implementation could be improved by instead of locking the AI to a certain range to the middle, letting impassable areas themselves generate repelling potential values. This was the original idea, but the map implementation in the game Formless made this difficult and unfortunately that had to be set to a lower priority.
5 User studies

To test the weight implementation (described in Section 1.1 and Section 4), a number of user studies were made.

5.1 Overview

6 similar tests were done with video game interested people from BTH in groups of four. All tests started with the four participants playing a match against each other in teams of two, to get to know the game Formless and how it is played. It was a free match, where regular items were unlocked, regular statistics were shown, and the participants were allowed to communicate.

After that, the real testing began. Two more matches were played. Before the first match, the participants quickly read through the questions of the survey, to be prepared what to look for. This was partly because the questions of the first and second match were the same, and knowing the questions before playing the second match but not before the first makes the conditions between the two matches unequal.

The point of playing these two matches, was to try out the weights. One of the matches had weights activated, one did not, and this was unknown to the participants. The order in which the two matches were played was also altered between different test sessions.

In both matches, all players (both human and computer controlled) got identical sets of two skills: one to attack with and one to heal with.

Both matches contained 8 players; the four participants and an AI unit each. Originally, player names are used to distinguish different players, but as that would give away which players are humans and which are not, different player names were replaced by different colours on the characters.

There are two teams, the red team and the blue team. To make out different players by colours, and still be able to see which team each character belonged to, a character kept its team colour which is shown in the original game, but got an aura in a different colour. Cyan, magenta, green and yellow were used to differentiate the four players in a team (hence the mentioning of those colours in the survey). These colours were randomly assigned before matches, and kept track of.
During the two test matches no communication was allowed, and the participants could not see each other's screens.

After the first match, the participants answered the corresponding first match questions in the survey. After the second match, they answered the corresponding second match questions in the survey, and they were all allowed to make changes to the answers in the first part.

### 5.2 Survey

The survey was divided into two parts, one part for each match. The exact same questions were used in both parts, and those questions are presented below.

1. **How did the cooperation generally appear between two AIs?**
   - A. They often healed each other and attacked together
   - B. They often healed each other but did not attack together
   - C. They didn't heal each other much but they attacked together
   - D. They did not cooperate

2. **How did an AI generally appear to cooperate with a human player?**
   - A. It often healed the player and attacked together with the player
   - B. It often healed the player but did not attack together with the player
   - C. It didn't heal the player much but it attacked together with the player
   - D. It did not cooperate
3. **How did a human player generally appear to cooperate with an AI?**
   A. He/she often healed the AI and attacked together with the AI
   B. He/she often healed the AI but did not attack together with the AI
   C. He/she didn't heal the AI much but he/she attacked together with the AI
   D. He/she did not cooperate

4. **How did the cooperation generally appear between two human players?**
   A. They often healed each other and attacked together
   B. They often healed each other but did not attack together
   C. They didn't heal each other much but they attacked together
   D. They did not cooperate

5. **Inflexible AI behaviour**
   Which of the following occurred?
   - An AI healed a team mate when it wasn't necessary
   - An AI stood around and did nothing
   - An AI did some poor target selecting when attacking
   - An AI rushed into a dangerous situation and got killed
   - An AI moved around too much
   - An AI stood still too much
   - None of the above

6. **Inflexible human player behaviour**
   Which of the following occurred?
   - A player healed a team mate when it wasn't necessary
   - A player stood around and did nothing
   - A player did some poor target selecting when attacking
   - A player rushed into a dangerous situation and got killed
   - A player moved around too much
   - A player stood still too much
   - None of the above
7. **Which players do you think were computer controlled?**

Mark the players you thought were AIs.

- Red team, yellow player
- Red team, turquoise player
- Red team, green player
- Red team, magenta player
- Blue team, yellow player
- Blue team, turquoise player
- Blue team, green player
- Blue team, magenta player

8. **What made you think that they were AIs?**

A text box for free writing was presented.

**Other comments**

A text box for free writing was presented.
5.3 Results

Some groups consisted of just 3 people because some of the people who signed up for the test did not show up. The author then jumped in to play with the participants, but did not answer the questions. All details regarding the test results can be found in Appendix B.

Presented below are some summaries of the test results, based on the information needed to test the hypotheses. The diagrams are based on the survey questions given in the previous section.

<table>
<thead>
<tr>
<th>Question</th>
<th>With weights</th>
<th>Without weights</th>
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<tr>
<td>4</td>
<td><img src="image7" alt="Pie chart" /></td>
<td><img src="image8" alt="Pie chart" /></td>
</tr>
</tbody>
</table>

Figure 5.2: The diagrams show the results of:

1. How the AI appeared to cooperate with other AIs
2. How the AI appeared to cooperate with human players
3. How a human player appeared to cooperate with an AI
4. How a human player appeared to cooperate with other human players
<table>
<thead>
<tr>
<th>Question</th>
<th>With weights</th>
<th>Without weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td><img src="image1" alt="Graph" /></td>
<td><img src="image2" alt="Graph" /></td>
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</tbody>
</table>

*Figure 5.3: The diagrams show the results of what inflexible mistakes the AI did in general.*

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<tr>
<th>Play order</th>
<th>Match 1</th>
<th>Match 2</th>
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<tr>
<td>Without weights first, with weights second</td>
<td><img src="image5" alt="Graph" /></td>
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</table>

*Figure 5.4: Answers given to question 7 in diagram form. Number of guesses on who was an AI.*
<table>
<thead>
<tr>
<th></th>
<th>With weights</th>
<th>Without weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>All combined results</td>
<td><img src="chart1.png" alt="Bar chart" /></td>
<td><img src="chart2.png" alt="Bar chart" /></td>
</tr>
</tbody>
</table>

*Figure 5.5: All answers given to question 7 in diagram form. Number of guesses on who was an AI.*

### 5.4 What is AI behaviour? - *Summary of participant comments*

Most of the comments on what made the participants think that someone was an AI, was typical AI mistakes that we were aware of but unfortunately did not have time to rectify. Examples of this are bumpy and stiff movement, standing still doing nothing when no other player was close, too fast reactions on respawn and inhuman accuracy.

A few other comments were made:

1. AIs were better at healing efficiently (and to remember to heal at all)
2. AIs grouped together more
3. AIs cooperated better with the entire team
4. AIs never ran away to save themselves when low on health
5. AIs tended to strictly follow human players instead of moving freely
6 Discussion

The final number of test participants was 20, which is not enough to scientifically prove anything, though some interesting patterns have arisen (shown in the diagrams in the previous section) that need to be analysed.

6.1 Test execution

Something that we noticed during the test sessions, was that the participants often had problems seeing which character was computer controlled, and which was a human player. The results of people guessing which was which in the survey also proves this.

We think this may have affected the results quite much more than we thought it would. Participants focused too much on trying to play the game and trying to guess who was an AI and who was not, and did not really have time to watch the behaviour of the AI closely. When the tests were prepared, it seemed like a good idea to not serve the participants with which was which to not let that affect the results, but afterwards the effect of that decision became the opposite of what we thought, and forced participants to guess a lot instead of analysing what they saw.

However, by making the distinguishing process difficult, we made sure that the behaviour of the AI was compared in its entirety with the corresponding human behaviour. Which is a good thing, since the goal of implementing an AI is to make it act humanly.

6.2 Test results

Looking at the diagrams in Figure 5.2, 5.3 and 5.4, a couple of patterns can be seen.

1. The AIs cooperated better together without weights.
2. An AI cooperated better with a human player with weights.
3. A human player cooperated better with an AI with weights.
4. The AI made different and slightly fewer inflexible mistakes when the weights were turned off.
5. It was generally harder to make out who was computer controlled and who was a human player when the weights were turned on.
6. It was generally easier to make out who was computer controlled and who was a human player the second match, no matter the order.
Reading from general comments by participants, AI’s grouped together more in the battles with weights turned off. This was expected, as with weights turned off, a team mate is always considered interesting, independent of its current health level. This may have been perceived as they cooperating more with each other.

The most interesting parts of Figure 5.3 are responses 2, 4, 5 and 6, since they consider movement, and movement is what the Potential Fields handle.

The AI seemed to get stuck (response 2) more often with the weights turned on (we thought the effect would be reverse).

Response 4 about AIs rushing did not show any significant difference between the two versions.

Response 5, “The AI moved around too much”, did not occur at all when the weights were turned off. This may be due to it grouping more with its team, not wandering off on its own, since the team mates always were interesting.

Response 6, “The AI stood still too much”, occurred more when the weights were turned off. This is highly related to the results of response 5; when team mates always are interesting, the ability to move around itself, searching for enemies, is reduced.

Response 7 shows that participants more often thought that “None of the above” had occurred during the battle without weights.

Figure 5.4 shows how good the participants were at guessing who was an AI. The first two rows both show that it was easier to guess the second match played, no matter the order of the matches. The improvement was minor in the second row, while quite big in the first row, which indicates that it was easier to guess in general with the weights turned off (which can also be read from row 3).

In Section 5.4 it is mentioned that the AIs occasionally stood still and did nothing. This occurred only, but not always, when no point of interest was in the AI’s visual field. We would like to note that this was supposed to be solved with the pheromone trail field, which should push the AI forwards when nothing else pulls it in a direction. Unfortunately, it seems that this did not work properly and that the AI still sometimes got stuck.
6.3 Research questions and hypotheses

The research questions were:

• To what extent can Potential Fields be used for AI calculations in a fast-paced, multiplayer arena-based game?

• What is the impact of using dynamic weights on Potential Fields, when multiple fields are used together?

And the corresponding hypotheses were:

• Potential Fields can be used as the only way of movement for the AI, and still make it appear to consider several different aspects at once.

• Dynamic weights balances the different Potential Fields, making the AI cooperate better with its team.

The first hypothesis can be quite easily answered: In the final implementation for the tests, Potential Fields were used as the only way of movement, and test participants still had problems seeing who was computer and who was human controlled. Therefore, we consider this first hypothesis to be true, though it would probably not have been the same if multiple fields had not been used.

The second hypothesis is more complex and needs more discussion.

6.3.1 Impact of weights

In theory, the purpose of the weights was for the AI to adapt to the current status of the battle, like humans do. Scoring kills is the objective of the game, therefore shooting at, and perhaps chasing, an enemy with low health is a good idea. We predicted that humans often all attack the same target if it is low on health, and that with the AI doing the same, it would appear to cooperate with the team to take down opponents.

By implementing the weights as we did, we made sure that team mates were not interesting if they had full health. This meant that the AI sometimes rushed into danger because it wanted to chase an enemy. Its own health was not considered at all. But by implementing the healing field weights like we did, we also made sure that the AI did not get stuck around a team mate that was just hanging around, but was free to explore on its own.
As it seems, the impact of the weights was not as positive as it sounded in theory; but on the other hand, the AI was never claimed to be better without them either by the participants. We think the difference would have been greater with fewer players in each game or a bigger arena, where there is not constantly a point of interest nearby.

The diagrams show that the AI appeared to cooperate better with human players with the weights turned on, which was the goal. The fact it was also the other way around, that a human player seemed to cooperate better with an AI when the weights were turned on, also speaks in favour of our hypothesis.

Yet this does not prove the hypothesis to be true, as an AI appeared to cooperate better with other AIs with the weights turned off.

The fact that it seems to have been harder to guess who was computer controlled and who was a human player with the weights turned on, could be seen as the AI being more adaptive and cooperating more, though this is not guaranteed.

The impact of the weights might have been quite much different if the AI’s own health status had been brought into the calculation, perhaps by making the opponents uninteresting or even repelling when the AI’s own health is low.

7 Conclusions

Due to the comments that it was hard to see which was an AI and which was a player, and that the AI was good at playing the game, a conclusion can be drawn that multiple Potential Fields do work well as a movement solution in this genre. Multiple fields in general is a good method of covering the many parts of a complex game.

The varying results of the user study conducted in Section 5 indicate that no clear conclusions can be drawn regarding the impact of weights at this time. It made a difference, but not a difference big enough to be highly noticeable by the participants or to prove the truth value of the second hypothesis.
8 Future work

Mentioned in Section 6 Discussion was that the tests may not have generated fair results to the impact of weights on Potential Fields. Therefore, it would be really interesting to see two tests conducted in parallel; one where participants had to guess on who was who, and one where participants knew that through the whole test.

It would also be interesting to see multiple Potential Fields used in other types of fast multiplayer games that are not in the RTS genre. As mentioned before, it is quite unexplored, and in general, they worked quite well for this implementation.

During the presentation we got some interesting ideas to further improve our implementation. One of the ideas was to use more pheromone trails, e.g. giving opponents an attracting pheromone trail for the AI to follow. This could make it easier for the AI to find opponents.

Another idea was to give all players, both opponents and team mates, a static potential around them, in the area where we can reach them, where the whole area has the same potential and opponents have a slight repelling potential and team mates a slight attracting. This extra field might prevent the AI to rush alone into a group of opponents.

These are great ideas that we might implement for the AI in the game in the future.

Lastly, more testing on weights would be interesting in all kinds of Potential Field situations. When do the weights improve and when do they deteriorate the behaviour of an AI? What happens if more variables are put into the weight calculation? Many new questions have arisen from studying this brief test.
References


Schwab, Brian 2009, *AI Game Engine Programming* 2nd edition, Course Technology, USA

Rabin, Steve et. al. 2002, *AI Game Programming Wisdom*, Charles River Media, USA


Graphs in Section 4 Implementation generated with *Wolfram Alpha* in April 2011, [http://www.wolframalpha.com/input/?i=y+%3D+-0.005x^2+%2B+3x+-+450](http://www.wolframalpha.com/input/?i=y+%3D+-0.005x^2+%2B+3x+%2B+450) [http://www.wolframalpha.com/input/?i=y+%3D+-0.005x^2+%2B+1.5x](http://www.wolframalpha.com/input/?i=y+%3D+-0.005x^2+%2B+1.5x)
Appendix A – *Formless BETA* concept document

Development team

7 students at the program *Game Programming* at Blekinge Institute of Technology, Karlskrona, Sweden.

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Introduction

- Formless is an intense multiplayer arena based action game
- You build your own character with different choices, and you can always change your mind at any time
- You play together with friends in teams of one or more players. In teams larger than one, cooperation is key
- In battle, all characters take different forms depending on player actions and happenings

Description

We are at a planet that was once populated by a great civilization, now only known as The Builders. These Builders built technologically advanced war robots, and went to war with each other, for a reason no longer known. These robots only existed for war and were built to fight anyone without a friendly identification. Now, an unknown amount of time later, all Builders are erased from the planet and all that is left is these war robots and some traces of the long gone civilization, and the robots will keep on attacking each other until the end of time.

The objective of the game is to wipe out other robot armies, and to gain items that will help you achieve the first mentioned task.

The items that are used are called *modules*. There are two types of modules: *active modules* and *passive modules*. Active modules unlocks skills (abilities) for the robot to use, while passive modules enhance the performance of the robot in different ways (such as movement speed).
Modules are equipped to the robot's core. There are different cores with different attributes and module slots.

![Screenshot of the inventory where core and modules are chosen](image1)

The robot also consists of particles of an unknown mass, that circles around the core, and that the core can control and shape. The particles are a kind of resource to the robot, which, among other things, protects the core and materializes the activation of skills.

![Screenshot of the lobby where the teams are built](image2)

A game is played in an arena with predefined rules. Up to eight players in two teams are thrown into the arena with the active modules they equipped at hand.
During 4 minutes, the players try to take down their opponents as many times as possible.

One type of abilities is special. As a player, you can link yourself with other players, creating a particle stream between you, which has different effects. The link on the picture heals a team mate, but if the link is broken (e.g. by Player3 in the opposing team walking through the link) the healing stops.

Also, all players and skills have different shapes, which is another of the game’s original features. The players’ shape is dependant on the core equipped, while the skill’s shape is dependant on what it does.

Features

• High pace and cooperation
• Different choices and combinations that results in many different game styles
• A playful graphical style with players taking many different forms depending on actions and happenings
• Link your character with other characters to create tripwires, blocking walls and other cool effects
Platform

PC, with a DirectX 10.1 graphics card or better

Controls

There is no target locking, you always have to aim with the mouse. Movement in the arena is done with the keys W, A, S and D. Activation of skills is done originally with keys 1-9, but can easily be reassigned to keys of the player’s choice.

Screenshot of the player using the skill “Hammer”, which will shortly slam down into the ground to the left.
Appendix B – Detailed test results

All combined results

A total of 20 participants.

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<th>Answer</th>
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<th>Answer</th>
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Table B.1: All answers given to questions 1 – 6 in text form.
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Table B.2: All answers given to questions 1 – 6 in diagram form.
Question 7, guesses on who was an AI

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Table B.3: All answers given to question 7 in diagram form. Number of guesses on who was an AI.
**Match 1 with weights, match 2 without**

*A total of 9 participants.*

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*Table B.4: Answers given to questions 1 – 6 in text form.*
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Table B.5: Answers given to questions 1 – 6 in diagram form.
Question 7, guesses on who was an AI

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Table B.6: All answers given to question 7 in diagram form. Number of guesses on who was an AI.
Match 1 without weights, match 2 with

*A total of 11 participants.*

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*Table B.7: Answers given to questions 1 – 6 in text form.*
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Table B.8: Answers given to questions 1 – 6 in diagram form.
**Question 7, guesses on who was an AI**

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*Table B.9: All answers given to question 7 in diagram form. Number of guesses on who was an AI.*