SEABirds: An AHP Approach to Solve the Angry Birds AI Challenge

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Abstract

SEABirds is an agent that can play Angry Birds autonomously and is competitive in the Angry Birds AI Competition. It mainly implements the *Analytic Hierarchy Process* (AHP), a decision making technique, which no other agent has before. The distinctive characteristic of this agent is the usage of AHP with background knowledge and heuristics, which gives modest results compared to other agents in the latest benchmark. In our evaluation, SEABirds outperforms 20 other agents from the benchmark, which all are realized using quite different approaches to solve the same 21 levels of the game.

1 Introduction

Angry Birds[1] enjoys a huge popularity since 2009. The objective is to destroy all pigs, which are usually protected by structures of different complexity and building materials. One can destroy pigs by hitting the structures or the pigs directly. This can be done by using a limited number of birds, launched in a slingshot and are targeted towards specific positions. The structures can be composed of different materials such as wood, ice and stone as well as the birds can be of different type, each having specific abilities. The principal idea of the game remains: the fewer birds are used to destroy all pigs and the more damage on structures is made, the higher the score.

Playing the game for a human player is challenging when it comes to having a higher score, but still remains fairly easy to destroy all the pigs. Though, humans need to approximate the trajectory, which needs quite some training to achieve adequate aiming accuracy. In order to obtain maximal reward, humans can rely on their experience and common sense reasoning with respect to physical principles; such as the effect of gravity on objects, structural analysis or excitement of consequence reactions. For computers the game remains overall challenging in most of theses aspects. Most of all, the (physical) consequences of each possible action is not known in advance and needs to be approximated.

The Angry Birds AI Competition[2] was created as a mean to invite everyone to propose different intelligent playing agents that would play the game without human intervention. On the long run, the goal of the competition is to build AI agents that could play new levels better than the best human players [Renz *et al.*, 2015].

2 Game Playing Observations

Several observations can be made while playing Angry Birds. Among the first things that one spots is that, there are five type of birds : *Red*, *Yellow*, *Blue*, *White*, *Black*.[3] One can also distinguish the type of material: *Ice*, *Stone*, *Wood*, *Pig*, *TNT*, and *Other*.[3] The main observations made for birds and the structure material are the following.

- *Wood* and *Ice* have similar hardness. *Stone* is the hardest material to destroy. Usually, it requires the usage of special birds or gravity to destroy them. *Pig*, *TNT*, and *Other* are usually easy to destroy.
- *Red* can not destroy *Wood* and *Stone*, but can bring down some blocks of *Wood*. It is able to destroy one block of *Ice*, but will lose momentum afterwards. It does not have any tap action.
- *Yellow* is specialized to destroy *Wood*. The relation with other materials is apparently similar with *Red*. *Yellow* will get some momentum if we click the screen when *Yellow* is flying. Therefore, tap action can be used to extend the distance covered by *Yellow*.
- *Blue* is specialized to destroy *Ice*. The relation with other materials apparently is similar with *Red* and *Yellow*. *Blue* has tap action to split into three *Blue*. It can be used to hit some targets at one time, although in very limited area.
- *White* is a bird that can drop a powerful egg. This egg will explode upon touching the ground, and gives quite a strong impact. The impact can even destroy *Stone*. Dropping an egg mechanism is a unique feature of this bird, because it can hit some positions in a level structure that are not reachable with other birds.

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[1] `https://www.angrybirds.com/`

[2] `http://aibirds.org/`

[3] We will simply identify the objects by using these names.

- *Black* can be considered as the most powerful bird. The bird itself seems really heavy as it can destroy any common material (even *Stone*) just using its momentum. Tap action for this bird will give a powerful explosion that can be used to destroy anything near it. If there is no tap action after slinging *Black*, it will also explode within some seconds.

Structure

A set of blocks (or objects) build up a structure. It is important to analyze how those blocks can realize a structure. Angry Birds uses a physics engine, so it simulates some phenomena such as gravity and momentum. These need to be taken into account as it will strongly support predicting what happens after a bird hits a structure.

In most cases, it is always easier to hit a standing block. It will ensure the block to fall down if it is not completely destroyed. Hence, it may at least cause a domino effect and hit other blocks. Laying block are harder to move, and it might be better to avoid hitting those objects.

Interaction between blocks in a structure realize some kind of supporting system. A block supports another block if its non-existence will lead to movement of another block. If we have a plan to destroy any block, hitting the supporting block should be an option.

TNT is a unique material. It helps destroying the structure, since hitting it will lead to an explosion. In general it is a good choice to aim at a *TNT* box.

Level Strategy

Except for some levels, a good strategy to get a high score is to use as few birds as possible. For each remaining bird, 10000 bonus points are emitted. Although by experience, there is a level where destroying structure will give more score than saving the birds.

The player also needs to maximize structure destruction in order to get a better score. Hence, it is in general better to destroy the pig by hitting supporting structure rather than hitting it directly. That being said, the player also needs to consider that it is more reliable to destroy a pig by directly hitting it.

3 AHP Based Approach

Analytic Hierarchy Process (AHP) is a method used in decision making that was originally created in the early 1970s, by Thomas L. Saaty. Since then, it has been used by many researchers in the field of decision making [Mon *et al.*, 1994], data mining [Liu and Shih, 2005] or machine learning [Partovi *et al.*, 1990; Cheng *et al.*, 2007; Marjanović *et al.*, 2011]. The general idea is that, the problems are decomposed into a hierarchy of criteria and alternatives [Haas and Meixner, nd]. With that being said, AHP is considered as a multi-criteria decision-making approach. The reason why it has attracted many researchers through years is due to its simplicity, which remains one of its main advantages. Another advantageous property is the fact that the required input data is easy to obtain [Triantaphyllou and Mann, 1995]. AHP itself is not a very complex decision support tool, but which in turn can be used to solve complex decision

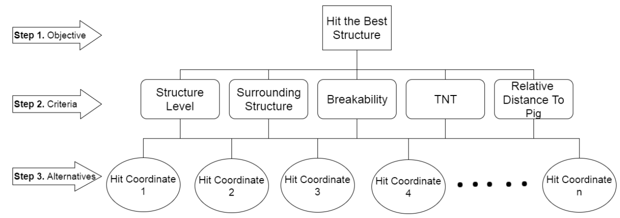

Figure 1: Hierarchy Tree of Hitting the Best Structure

problems. In summary, AHP provides a logical framework to determine the benefits of each alternative. The process consists of the following steps:

1. **State the objective** for which a decision has to be made. In our case, since we consider only a single shot, the goal would be to *Hit the Best Structure*.
2. **Define the criteria** considered for determining a decision. We mainly rely on the following criteria:
   - *Structure Level* denotes the Y-axis position of a structure. In the following this criterion is denoted with *StLe*.
   - *Surrounding Structure* denotes how many structures are located around a structure. This criterion is denoted with *SuSt*.
   - *Breakability* denotes how well the current bird suits for hitting the targeted structure, subsequently this criterion is denoted with *Br*.
   - *Relative Distance to Pig* denotes the distance of a structure to the pigs. It also considers relative position to the pig. The structure below or on the right side of a pig will get a smaller score in this criterion, because usually the left one causes higher damage due to the direction of the flight. Moreover, if the structure is a pig, it will get a high score. This criterion is denoted with *ReDi*.
   - *TNT* indicates whether an object is a TNT, or not. This criterion is denoted with *TNT*.
3. **Pick the alternatives** over which the decision has to be made. Intuitively, we consider all structures / objects (of the current state) as possible target, and therefore as alternatives to choose over.

Figure 1 indicates the hierarchical organization of the involved steps, which will be used to decide which object to target at.

4 Calculating the Criteria and Alternatives

The original AHP method implementation requires to follow four steps of which the first two are already stated above. It is basically required to define the problem and to create the decision hierarchy tree [Saaty, 1990]. Now, the challenging bit is to determine the relative importance of the criteria. In this particular case, there are five criteria and one has to decide which one is more important than the other having in mind a single shot. These two final steps (Step 3 & 4) are the computation of the criteria and alternative ranking. For a given list of n criteria, a $n \times n$-pairwise comparison matrix needs to be defined, which depicts the relative importance of one criterion over another. The values are obtained from the fundamental scale represented in [Saaty, 1990]. We elaborated the following comparison matrix for our aforementioned criteria.

$$M = \begin{array}{c} \\ \textit{Br} \\ \textit{SuSt} \\ \textit{ReDi} \\ \textit{StLe} \\ \textit{TNT} \end{array} \begin{array}{c} \begin{array}{ccccc} \textit{Br} & \textit{SuSt} & \textit{ReDi} & \textit{StLe} & \textit{TNT} \end{array} \\ \begin{pmatrix} 1.0 & 2.5 & 0.1 & 1.4 & 3.3 \\ 0.4 & 1.0 & 0.2 & 1.4 & 2.5 \\ 6.0 & 4.0 & 1.0 & 10.0 & 2.0 \\ 0.7 & 0.7 & 0.1 & 1.0 & 1.1 \\ 0.3 & 0.4 & 0.5 & 0.9 & 1.0 \end{pmatrix} \end{array}$$

Given this matrix, we compute its *eigenvector* as follows:

1. Let M_S be M raised to powers that are squared.
2. The row sums of M_S are calculated and normalized, yielding a $n \times 1$-matrix (*eigenvector*).
3. Apply the first and the second steps for M_S iteratively.
4. Terminate, if the difference (absolute value) between the row sums of two consecutive calculations is smaller than or equal to a prescribed value (here 0.002). The final normalized row sums denote the expected $eigenvector$ representing the criteria ranking. For M this yields:

$$\begin{array}{c} \\ \textit{Br} \\ \textit{SuSt} \\ \textit{ReDi} \\ \textit{StLe} \\ \textit{TNT} \end{array} \begin{array}{c} \begin{array}{ccccc} \textit{Br} & \textit{SuSt} & \textit{ReDi} & \textit{StLe} & \textit{TNT} \end{array} \\ \begin{pmatrix} 1.0 & 2.5 & 0.1 & 1.4 & 3.3 \\ 0.4 & 1.0 & 0.2 & 1.4 & 2.5 \\ 6.0 & 4.0 & 1.0 & 10.0 & 2.0 \\ 0.7 & 0.7 & 0.1 & 1.0 & 1.1 \\ 0.3 & 0.4 & 0.5 & 0.9 & 1.0 \end{pmatrix} \end{array} \Longrightarrow \begin{array}{c} \\ \textit{Br} \\ \textit{SuSt} \\ \textit{ReDi} \\ \textit{StLe} \\ \textit{TNT} \end{array} \begin{array}{c} \text{CPR} \\ \begin{pmatrix} 0.1471 \\ 0.1032 \\ 0.589 \\ 0.0695 \\ 0.0912 \end{pmatrix} \end{array}$$

The CPR vector is computed only once, every time an update to the criteria matrix was done. We do not use different matrices yet, but rather tackle all levels with the same. Contrary, for each game state and possible shot the alternative ranking is computed which yields the targeted object. Essentially, the alternative ranking is obtained as follows:

1. For each alternative, assign value for each criterion, which is obtained based on heuristics (experience by playing the game). For m alternatives and n criteria, we obtain a $m \times n$-matrix.
2. We then actually need to normalize the alternative values for each criterion; i.e. we compute the normalized value $x'_{i,j}$ of alternative j and criterion i as follows:
$$x'_{i,j} = \frac{x_{i,j}}{\sum_{k=1}^{n} x_{i,k}}$$
3. Multiply this matrix with the previously determined criteria ranking, sucht that again we obtain a vector of ranked alternatives of which we pick the one with the highest value – the targeted object.

An example of this computation is given in the following. Two alternatives *Obj*$_1$ and *Obj*$_2$ are used and their criteria value asserted; i.e. breakability of *Obj*$_1$ and *Obj*$_2$ are more similar than their value for the remaining criteria. The first alternative has a bonus score as a *TNT*, but worse scores for

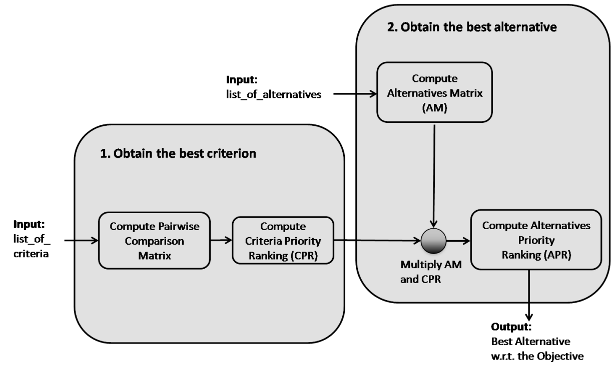

Figure 2: The process for obtaining the best alternative

other criteria. The second alternative is located in the lower part of the structure, also surrounded by other structures and near to the pigs. The Alternatives Priority Ranking (APR) is obtained by multiplication of the alternatives matrix (1) and the CPR.

$$\begin{array}{c} \\ \textit{Obj}_1 \\ \textit{Obj}_2 \end{array} \begin{array}{c} \begin{array}{ccccc} \textit{Br} & \textit{SuSt} & \textit{ReDi} & \textit{StLe} & \textit{TNT} \end{array} \\ \begin{pmatrix} 0.4 & 0.2 & 0.3 & 0.3 & 0.9 \\ 0.6 & 0.8 & 0.7 & 0.7 & 0.1 \end{pmatrix} \end{array} \times \tag{1}$$

$$\begin{array}{c} \\ \textit{Br} \\ \textit{SuSt} \\ \textit{ReDi} \\ \textit{StLe} \\ \textit{TNT} \end{array} \begin{array}{c} \text{CPR} \\ \begin{pmatrix} 0.1471 \\ 0.1032 \\ 0.589 \\ 0.0695 \\ 0.0912 \end{pmatrix} \end{array} = \begin{array}{c} \\ \textit{Obj}_1 \\ \textit{Obj}_2 \end{array} \begin{array}{c} \text{APR} \\ \begin{pmatrix} 0.3591 \\ 0.6409 \end{pmatrix} \end{array} \tag{2}$$

In addition, for a better understanding of the process for obtaining the best alternative, Figure 2 summarizes the required inputs, the output and the steps in between.

Briefly, we want to mention how the criteria values for each alternative is obtained. First, for *StLe* we simply use the Y-coordinate of the considered object (conveniently the coordinates are taken from the framework's vision component). Then, for *SuSt*, the objects with distance less than 30 pixels are collected. *Br* is defined manually; i.e. for each combination between object type and birds we use a predefined breakability value. *ReDi* is the direct relative distance to the pigs.

Figure 3 provides another example, where for the given scene we are able to determine the best (first) shot (to the best of our knowledge).

5 Evaluation

In order to be able to compare the performance of our SEABirds agent with the ones from the benchmarks, the agent was run three times throughout all the 21 levels of the Poached Eggs collection. The time constraints of the competitions were taken into consideration. Hence, any of the three runs did not take longer than 1 hour to finish all levels.

In the first run, the total score of all the 21 levels is 911710. In the second run, the total score of all the 21 levels is 934620,

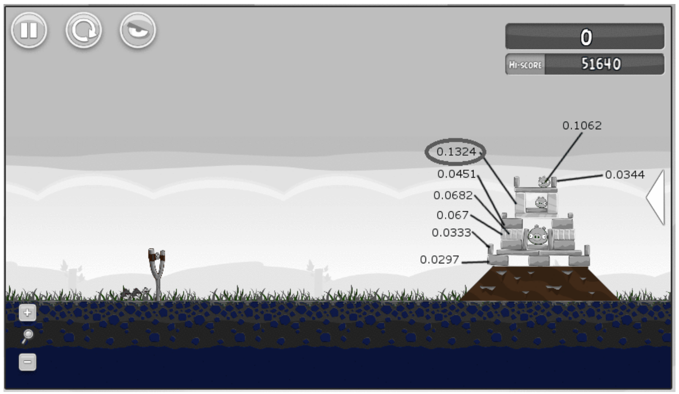

Figure 3: AHP result for level 1–13. SEABirds would target the marked object (center coordinates).

while in the last run, the total score of the 21 levels is 942170. In this case, to have a better representation of the performance of SEABirds agent, the average of all these three runs was computed and the total score for all the 21 levels is 929500.

In Table 1 one can see the scores for all the 21 levels of the Poached Eggs collection, in each of the three runs. The first column indicates all the levels from 1 to 21, denoted as $L_1, L_2, ..., L_{21}$ and each of them stands for *Level 1, Level 2,...Level 21*, respectively. The last one TS stands for Total Score of the 21 levels. While the other column states the obtained score in each level of the corresponding run. We consider the average score from the last column to compare SEABirds with that of the benchmarks.

In addition, after having the average score of SEABirds performance, the same was compared with the Benchmarks taken from the latest competition [Competition, 2016]. The results of comparison are bestowed in Table 2. Given those results, SEABirds was ranked on the 11th place, taking the place of *Luabab* agent whose total score is 894840, while SEABirds has a total score of 929500. Observing closely the results listed in Table 2, on the first column are listed all the teams indicated by their names while in the second column are the total scores they obtained.

One may also notice that the teams are ranked from the one with the highest score, starting from top-down, to the one with the lowest score. Therefore, PlanA+ has a total score of 1002380. While, the second one has a score of 981120, and so on. Even if in this table SEABirds is the last, still, this might be considered as a modest result, since in the original benchmarks ranking our agent performs better than 20 other agents.[4]

Furthermore, second set of 21 poached eggs levels is used for another benchmark. The result is shown by Table 3. The agent achieved 695460 for the total score. The agent could not solve all 21 levels in 1 hour time limit. Based on the benchmark from the website, the agent is placed on the 3rd position. The score is similar with AngryBER as the old 3rd position (682530) and 2nd position, Plan A+ (703650).

[4]`https://aibirds.org/benchmarks.html`

	1st Run Score	**2nd Run Score**	**3rd Run Score**	**Average of Runs**
L1	30390	30390	30390	30390
L2	53750	53750	53750	53750
L3	40470	40470	40470	40470
L4	27970	27670	28190	27943.3
L5	64820	64820	64820	64820
L6	15430	27390	33520	25446.6
L7	30550	29870	37020	32480
L8	37750	44930	35310	39330
L9	35040	41600	42710	39783.3
L10	31450	34820	44840	37036.6
L11	43730	47270	47270	46090
L12	53600	53600	53210	53470
L13	47570	47800	47800	47723.3
L14	65640	65640	65640	65640
L15	47220	40080	48810	45370
L16	60000	52150	53700	55283.3
L17	40790	38490	40600	39960
L18	42700	40130	44010	42280
L19	27700	31100	26710	28503.3
L20	38850	54050	42620	45173.3
L21	76290	68600	60780	68556.6
TS	911710	934620	942170	929500

Table 1: SEABirds Level Scores.

Team	**Total Score**
PlanA+	1002380
DataLab Birds	981120
AngryHex (2013)	974670
WISC	963160
AngryHex (2014)	960320
Angry Concepts	954030
Beau Rivage	952390
HungryBirds	951440
AngryBER	935330
RMIT RedBacks	933120
SEABirds	929500

Table 2: Total score compared the total score of other teams.

	Run Score		**Run Score**
L1	60500	L12	43200
L2	0	L13	73370
L3	102840	L14	36660
L4	0	L15	0
L5	66880	L16	0
L6	0	L17	27640
L7	52970	L18	0
L8	55380	L19	0
L9	21310	L20	0
L10	0	L21	73030
L11	81680	TS	695460

Table 3: Second set of 21 Poached Eggs levels.

6 Conclusion

Following the Angry Birds AI Competition on developing an AI agent that would successfully beat the best human player, the SEABirds agent was implemented using the AHP method. The reason for using AHP as a decision making supporter of our implementation, is because of its many advantageous properties. Among those, the fact that it is easy to compute and it gives surprisingly satisfying results, also in many other application domains where it was applied.

Before implementing AHP, the steps that would lead to satisfying results were carefully analyzed. As previously stated, the SEABirds agent will choose the object in a structure with the highest score and after each successful shot, will check for the remaining pigs. If there are remaining pigs, it will start from the beginning. AHP is used as a tool to find the right coordinate where to (exactly) hit the best object. The computations used in AHP in order to find the target object are explained in detail in Section 4.

Our implementation was compared with agents from the official competition benchmarks. The latest is presented in Section 5. The total score was quite promising compared to 20 other agents that our agent outperformed. Moreover, it is interesting to mention that to the best of our knowledge, there is no other team that competed on the competition and used AHP as their method for decision making.

7 Future Work

Attaining good results using AHP approach is motivational enough to give even more insights on how the SEABirds agent could be improved. Naturally, one could expand the set of criteria used in our implementation, such as considering orientation of an object (vertical or horizontal). It would also be conceivable, to use dedicated criteria and therefore a dedicated criteria priority ranking for certain type of levels / structures. This would require to classify the level and choose the criteria ranking thereon. The AHP method could be combined with a machine learning approach to choose the pairwise comparison values. Even though human-based values seem to work quite well, depending on the expert level. What has not been considered yet, but seems to be unavoidable, is a planning component over a sequence of shots, which has been done already by some other agents.

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