Qualitative Physics in Angry Birds: first results

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Abstract. Angry Birds is a well known game in which the main aim is to destroy all pigs located in a given level using a slingshot and birds of various kinds. In most cases pigs are positioned among other objects - building blocks, rocks or specifically profiled ground - whose behaviour reflects the laws of physics. The game rewards chariness of a player - the less birds she uses and the more damage she does to the whole structure in the level, the higher score she gets.

In our paper, we attempt to indicate the essential factors playing role in the process of destruction. Thus, we provide definitions of *influence* (which we further divide into two categories - *horizontal impact* and *vertical impact*), *stability* and *connection points*. Whereas the latter two can be evaluated regardless of what shot we will actually take, the former requires an assumption about the shot and it is counted by means of iterative analysis involving two central concepts - *propagation of force* (in the case of horizontal impact) and *center of rotation* (in the case of vertical impact).

The ultimate goal of the whole procedure is assigning each object which is reachable by a shot a numerical value expressing the scale of damage it does once hit. The playing program is then supposed to shoot at the object with the highest value.

1 Introduction

Angry Birds game gained popularity thanks to its simple rules and the behaviour of the game environment reflecting the laws of physics. The main aim in each level is, having a bundle of birds (sometimes of various kinds) at hand, to kill all the pigs, doing as much damage to other objects as possible. Usually pigs are not exposed to direct shots - in these situations one first has to get through sheltering structures protecting a pig. Since the number of birds we have at our disposal (our ammo) is each time limited, we need to carefully select points we want to shoot at. A bad choice can result in a pig surviving the whole cannonade. If we take a closer look at difficulties the game can cause to players of both types - human and AI - it turns out that what is the toughest task for a human agent - hitting the selected target - for an AI agent is a matter of routine. Indeed, having the object picked, a program can easily attune angle and power of the shot using patterns known from simple Newtonian physics. The choice of an object worth targeting at is, however, much tougher for an AI agent, notwithstanding the fact that humans often make it intuitively without serious trouble. The aim of this paper is, therefore, to introduce an algorithm that reflects human-like reasoning while picking out objects that are most valuable from the strategic point of view.

In existing literature on space representation (also in papers concerning Angry Birds) many qualitative approaches are presented. Several most notable examples are: $\mathcal{RCC}-8$ ([7]), Allen's Interval Algebra (primarily introduced as representation of the flow of time, see [1]), Rectangle Algebra ([2]) or the 4-Intersection Method ([3]). Despite their qualitative nature (which could presumably imply that they resemble human reasoning) they struggle with certain common difficulties, namely relatively low expressive power. In the context of such a complex problem like modelling behaviour of a set of objects in a dynamic environment they are insufficient in most cases. Thus, both $\mathcal{RCC}-8$ and the 4-Intersection Method can only express topological information (*A overlaps B*, *A is disconnected from B etc.*), whereas Rectangle Algebra - captures both topological and directional properties of rectangles (like, e.g., *to be above* or *to be to the left*, cf. [8, 9]) but leaves "untouched" the issue of mutual physical impact of the objects (for instance, *A has a horizontal impact on B of value n*) which usually can be evaluated in a dynamic context. A rather fruitful attempt of exploiting an extended version of the Interval Algebra and Rectangle Algebra can be found in [8, 9]. However, these tools are the most efficient in the case of blocks positioned orthogonally to two main axes. Usually such layout can only be found in an initial situation (before the first shot) in each level. After the first shot, often introducing a high level of entropy to the construction of blocks, most objects are positioned slantwise.

In this paper we focus not only on the initial layouts of block constructions but we also take into account more messy arrangements after the shots being taken. The main goal we want to achieve is attributing a unique numerical value to each object reachable by a shot. Consequently, object with the highest number - representing its highest strategic value - is chosen to be shot at in the first place. Our approach is both qualitative and quantitative. Qualitative because we qualitatively pick factors which, in our opinion, play the key role in the process of destruction carried out in the game. Hence, we distinguish and scrutinize the "static" notions: *stability* (involving the notions of *mass* and relative location) *shelter*, *being above* or *touching* and the "dynamic" notions: *horizontal* and *vertical impact* (with, respectively, *force propagation* and *center of rotation* as their central concepts). The process of selection of such key values is of qualitative nature as well as assigning them weights when calculating their overall impact on the whole arrangement. Quantitative factor of the approach is expressed by a numerical character of all patterns used to count the final value of a block. Certain inspirations from naive or qualitative physics (cf. [4, 6, 5]) can also be traced in our proposal.

2 Representation

Since the final choice of the best shot in an Angry Birds gameplay is based mainly on objects' spatial configuration, it follows that space representation of Angry Birds level plays a significant role here. The vision module provided by Angry Birds Competition organizers enables to extract all objects from a gameplay scene, i.e. to determine

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their contours, center points, etc. Our approach extends this quantitative representation and involves more abstract qualitative relations such as: “object o_1 touches o_2”, “object o_1 is above o_2” or “object o_1 is a shelter for o_2”. Such qualitative representation is more natural for human cognition and seems to be essential for a human while playing Angry Birds.

2.1 Quantitative representation

The provided vision module enables us to calculate the following quantitative data:

- $O = \{o_0, o_1, \ldots\}$ – the set of all objects, i.e. the set containing blocks, pigs, hills and ground, where each object o_i is identified with points inside o_i, i.e. $o_i = \{p_i \mid p_i \in o_i\}$,
- $center(o_1)$ – the center point of o_1 object, i.e. the center of o_1 mass
- $area(o_1)$ – an area of o_1 object,
- $x(p)$ – the x coordinate of a point p,
- $y(p)$ – the y coordinate of a point p,
- $dist(p_1, p_2)$ – distance between points, i.e. the number of pixels between p_1 and p_2,
- $dist(o_1, o_2)$ – distance between an object o_1 and an object o_2, i.e. $dist(o_1, o_2) = \min_{p_1 \in o_1, p_2 \in o_2} dist(p_1, p_2)$,
- $dist(p, o_1)$ – distance between a point p and an object o_1, i.e. $dist(p, o_1) = \min_{p_1 \in o_1} dist(p, p_1)$,
- $width(o_1)$ – width of a Minimal Bounding Rectangle (MBR) for an object o_1 – see Fig. 1,
- $height(o_1)$ – height of a Minimal Bounding Rectangle (MBR) for an object o_1 – see Fig. 1,
- $object\_type(o_1)$ – a type of an object o_1, i.e. ice, $wood$, $stone$ or pig,
- $B = \{b_1, b_2 \ldots\}$ – the set of all birds,
- $bird\_type(b)$ – a type of a bird b, i.e. red, $blue$, $yellow$, $white$ or $black$.

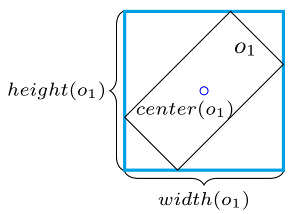


Figure 1: The object o_1, its center of mass and MBR’s height and width.

Additionally, the trajectory module provided by the organizers enables us to determine $traj(o_1) = \{traj_{\rightarrow}(o_1), traj_{\nearrow}(o_1)\}$, i.e. a set of 2 trajectories (low and high) of a shot targeted at the center of o_1, where $traj_{\rightarrow}(o_1) = \{p_0, p_1, p_2, \ldots\}$ is a set of points that belong to the low parabola trajectory and $traj_{\rightarrow}(o_1) = \{p_0, p_1, p_2, \ldots\}$ is a set of points that belong to the high parabola trajectory.

In the paper, we use the following notation:

- $o_0, o_1, o_2, \ldots$ for objects, with o_0 reserved for ground
- $O_1, O_2, \ldots$ for sets of objects,
- $p, p_0, p_1, p_2, \ldots$ for points,
- B for the set of all birds,
- $b, b_0, b_1, b_2, \ldots$ for birds.
- T for the set of all trajectories,
- $t, t_0, t_1, t_2, \ldots$ for trajectories.

2.2 Qualitative representation

We define *touch* – a binary relation between objects. Intuitively, two objects *touch* each other whenever they have a common point. However, since the computer vision component of the game playing software does not always precisely identify objects’ location, we also consider objects that do not have any common point, but the distance between them is smaller than a constant c (c is about 2 pixels), being in *touch* relation – see Definition 3.

Definition 1 (*touch* relation)**.**

$$\forall o_1, o_2 \in O(o_1 \neq o_2 \rightarrow (touch(o_1, o_2) \equiv dist(o_1, o_2) < c))$$

Obiously, the *touch* relation is irreflexive and symmetric. As an example consider the block structure presented in Fig. 2, where o_1 touches o_2, o_4 and o_0 (ground), therefore the following statements are true: $touch(o_1, o_2)$, $touch(o_1, o_4)$, $touch(o_1, o_0)$.

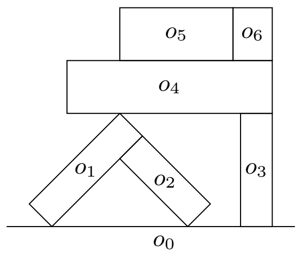


Figure 2: A sample block structure.

For any two objects o_1, o_2 that are in *touch* relation, we determine a set of connection points i.e. a set of points that are simultaneously very close to o_1 and o_2 (closer than the constant distance c). More precisely, we define a function $connection\_p : O \times O \rightarrow \{p_0, \ldots, p_n\}$, as presented in Definition 2.

Definition 2 (*connection_p* function)**.**

$$\forall o_1, o_2 \in O(connection\_p(o_1, o_2) = \{p \mid dist(p, o_1) < c \wedge dist(p, o_2) < c\})$$

Definition 3 (*touch* relation)**.**

$$\forall o_1, o_2 \in O(touch(o_1, o_2) \equiv (o_1 \neq o_2 \wedge connection\_p(o_1, o_2) \neq \emptyset))$$

Furthermore, we determine 3 significant points that belong to $connection\_p(o_1, o_2)$, i.e. the leftmost, rightmost and center connection points, by means of functions presented in Definitions 4, 5 and 6.

Definition 4 ($left\_p$ function)**.**

$$\begin{aligned} left\_p(o_1, o_2) = p \mid p \in connection\_p(o_1, o_2) \\ \wedge x(p) = \min_{p_i \mid p_i \in connection\_p(o_1,o_2)} x(p_i) \\ \wedge y(p) = \frac{1}{2} \cdot \Bigg(\min_{\substack{p_j \mid p_j \in connection\_p(o_1,o_2) \\ \wedge x(p_j) = x(p)}} y(p_j) \\ + \max_{\substack{p_j \mid p_j \in connection\_p(o_1,o_2) \\ \wedge x(p_j) = x(p)}} y(p_j) \Bigg). \end{aligned}$$

Definition 5 ($right\_p$ function)**.**

$$\begin{aligned} right\_p(o_1, o_2) = p \mid p \in connection\_p(o_1, o_2) \\ \wedge x(p) = \max_{p_i \mid p_i \in connection\_p(o_1,o_2)} x(p_i) \\ \wedge y(p) = \frac{1}{2} \cdot \Bigg(\min_{\substack{p_j \mid p_j \in connection\_p(o_1,o_2) \\ \wedge x(p_j) = x(p)}} y(p_j) \\ + \max_{\substack{p_j \mid p_j \in connection\_p(o_1,o_2) \\ \wedge x(p_j) = x(p)}} y(p_j) \Bigg). \end{aligned}$$

Definition 6 ($center\_p$ function)**.**

$$\begin{aligned} center\_p(o_1, o_2) = p \mid p \in connection\_p(o_1, o_2) \\ \wedge x(p) = \frac{1}{2} \cdot (x(left\_p(o_1,o_2)) + x(right\_p(o_1,o_2))) \\ \wedge y(p) = \frac{1}{2} \cdot \Bigg(\min_{\substack{p_j \mid p_j \in connection\_p(o_1,o_2) \\ \wedge x(p_j) = x(p)}} y(p_j) \\ + \max_{\substack{p_j \mid p_j \in connection\_p(o_1,o_2) \\ \wedge x(p_j) = x(p)}} y(p_j) \Bigg). \end{aligned}$$

As an example consider the structure presented in Fig. 3, where o_1 touches o_2, therefore we can determine the set of connection points $connection\_p(o_1, o_2)$ and among them: the leftmost, rightmost and center connection points. In this example we have $p_1 = left\_p(o_1, o_2)$, $p_2 = right\_p(o_1, o_2)$ and $p_3 = center\_p(o_1, o_2)$. Note also that in the case horizontally adjacent object $left\_p$, $center\_p$ and $right\_p$ collapse to a single point, namely the point located in the "middle" of the $connection\_p$ set. It is justified by the fact that we only distinguish between particular connection points when we are searching for *rotation centres*, which is inherently connected with vertically adjacent objects.

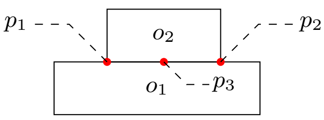


Figure 3: $left\_p$, $center\_p$ and $right\_p$ connection points between objects o_1 and o_2.

We define the upper edge of an object o_1 as a set of points $\{p_0, \ldots, p_n\}$ such that for each $i \in \{0, \ldots, n\}$, p_i belongs to the o_1 contour and a point directly above p_i does not belong to the o_1. The upper edge of an object is determined by the function $upper\_edge : O \to \{p_0, \ldots, p_n\}$ defined below.

Definition 7 ($upper\_edge$ function)**.**

$$\begin{aligned} \forall o_1 \in O(upper\_edge(o_1) = \{p \in o_1 \mid \\ \forall p_1(p_1 = \langle x(p), y(p)+1 \rangle \to p_1 \notin o_1). \end{aligned}$$

A pictorial presentation of the $upper\_edge$ of objects of various shapes is presented in Fig. 4.

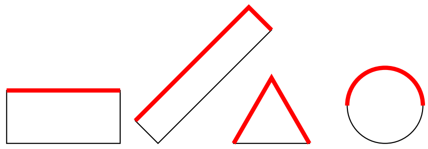


Figure 4: $upper\_edge$ for objects with various shapes.

Now we can define $above$ – a binary relation between objects. The intuitive meaning of $above(o_1, o_2)$ is that o_1 lies on o_2, i.e. o_2 is pressed by o_1 weight. A formal definition of the $above$ relation is given below.

Definition 8 ($above$ relation)**.**

$$\begin{aligned} \forall o_1, o_2 \in O(above(o_1, o_2) \equiv touches(o_1, o_2) \\ \wedge\, center\_p(o_1, o_2) \in upper\_edge(o_2)) \end{aligned}$$

The $above$ relation is obviously irreflexive and asymmetric. It should be clarified that $above(o_1, o_2)$ is not equivalent to the statement that o_2 is a support for o_1, e.g. in Fig. 2 we have $above(o_1, o_2)$ but at the same time o_1 is a support of o_2 (even though, due to asymmetry of $above$, it is not the case that o_2 is above o_1. The $above$ relation will play a significant role in our reasoning algorithm, therefore it needs to be understood correctly and cannot be confused with a support relation. We will denote a transitive closure of the $above$ relation by $above^{\star}$, which is obviously irreflexive, asymmetric and transitive.

2.3 Shelters

In Angry Birds it often appears that there is no other way of hitting a pig than destroying its sheltering structure first. It is then reasonable to define sheltering objects and to distinguish the most important shelter. We define $shelter$ – a ternary relation between two objects and a trajectory which denotes the fact that the first object is a shelter for the second object (always a pig) with respect to a given trajectory. Intuitively, $shelter(o_1, o_2, t)$ means that we cannot directly shoot a pig o_2 using trajectory t, because o_1 stands in the way leading to o_2, i.e. o_1 is situated on the trajectory t before o_2. More precisely, $shelter(o_1, o_2, t)$ whenever o_2 is a pig and o_1 lies on one of trajectories estimated by the trajectory module for a shot aiming at o_2. A formal definition of the $shelter$ relation is as follows.

Definition 9 ($shelter$ function)**.**

$$\begin{aligned} \forall o \in O \forall t \in T(t \in traj(o) \wedge pig(o) \\ \to shelter(o, t) = [o_1, \ldots, o_{n-1}, o_n]), \end{aligned}$$

where o_n is located nearest to o and the lower the index of an element in the sequence, the further the element is located from o.

Furthermore, for each object we determine a shelter value which allows us to distinguish between more and less important shelters.

We define a function $shelter\_val : O \to \mathbb{R}$ that maps an object into its shelter value. A shelter value of o_1 increases as the distance to the sheltered pig o_2 decreases, the number of objects between o_1 and o_2 decreases or the number of pigs sheltered by o_1 increases. The formal definition of $shelter\_val$ is presented below.

Definition 10 ($shelter\_val$ function)**.**

$$\forall o_1 \in O\Bigg(shelter\_val(o_1) = \sum_{\substack{o_2 \mid \exists t \\ o_1 \in shelter(o_2,t)}} \max_{t \mid o_1 \in shelter(o_2,t)} \frac{1}{dist(o_1,o_2)} \cdot \frac{1}{no\_between(o_1,o_2,t)+1}\Bigg),$$

where $no\_between(o_1, o_2, t)$ is a number of objects between o_1 and o_2 on trajectory t.

As an example consider Fig. 5. On a trajectory t_1 there are 2 shelters for the o_4 pig, namely o_2 and o_3. However, o_3 has the highest $shelter\_val$ because it is closest to the o_4 pig and there is no other shelter on the trajectory t_1 between o_3 and o_4.

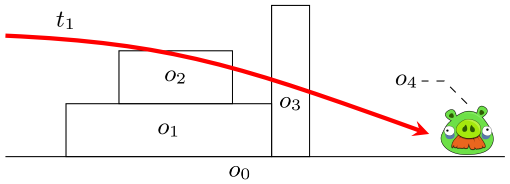


Figure 5: o_2 and o_3 are shelters for the o_4 pig, while considering t_1 shooting trajectory.

2.4 Stability

Stability is a quality of an object, which represents how hard it is to move it, e.g., by hitting it with a bird or another object. The object's o_1 stability increases whenever the number and stability of objects directly below o_1 increases, o_1 ratio of width to height increases, the cumulated mass of o_1 and all objects above o_1 increases, and a cumulated mass of the objects directly to the right of o_1 increases. Formal definition of a function $stability : O \to [0, 1]$ that assigns each object a stability value from the interval $[0, 1]$ (where 0 means that the object will move without any stimuli, while 1 means that the object is impossible to move) is presented below.

Definition 11 ($stability$ function)**.**

$$\forall o_1 \in O\Bigg(stability(o_1) = \Bigg(\frac{card(\{o_2 \mid above(o_1,o_2)\})}{\sum_{o_2 \mid above(o_1,o_2)} \frac{1}{stability(o_2)}} \cdot ratio(o_1) \cdot mass(o_1)\Bigg)^{\frac{1}{1+\max_{o_2 \mid on\_right(o_2,o_1)} area(o_2)\rho(o_2)}}\Bigg),$$

where

$$\forall o_1 \in O\left(ratio(o_1) = \begin{cases} 1 & \text{if } width(o_1) \geq height(o_1) \\ \frac{width(o_1)}{height(o_1)} & \text{otherwise} \end{cases}\right),$$

$$\forall o_1 \in O\left(mass(o_1) = \frac{1}{1 + \sum_{o_2 \in \{o_2 \mid o_1 \vee above(o_2,o_1)\}} area(o_2)\rho(o_2)}\right),$$

$$\forall o_1, o_2 \in O(on\_right(o_1, o_2) \equiv touch(o_1, o_2) \wedge x(connection\_p(o_1, o_2)) > x(center(o_1)),$$

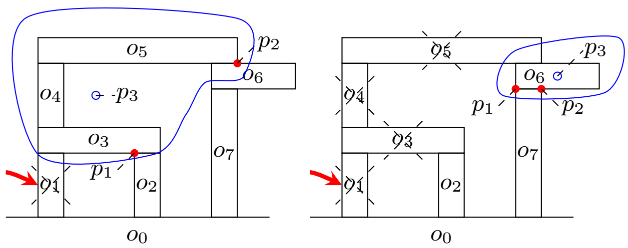
and $\rho(o_1) : O \to [0, 1]$ maps an object into qualitative classes of density, namely $\rho_{ice}, \rho_{wood}, \rho_{stone}, \rho_{pig}$.

3 Reasoning

In order to choose the best shot possible, we reason as follows. We have decided that there are two main types of objects which are of much interest to us. First and foremost we are interested in pigs, but we are also interested in blocks which constitute shelters for the pigs. We assign a value to each object based on how it influences above-mentioned objects (see section 3.3 for more details). We choose the object which has the highest value as our target. We calculate the influence of one object on another by means of its vertical impact and horizontal impact which will be discussed in the following two sections.

3.1 Vertical Impact

In many cases blocks are placed in such a way, that hitting one of them leads to a collapse of a number of others. In order to determine such an influence one need to consider how blocks are located with respect to each other. While quantitative method of calculating exact forces values that appears in a structure requires a lot of effort and afterwards leads to a high computational complexity reasoning algorithms, we have established our own qualitative physics method. Our method, called Vertical Impact, considers what would have happen if one of blocks in a structure would disappear (fall or be destroyed). Consider a situation presented on Fig. 6 a), i.e. a situation when the o_1 block is hit, and as a result it is destroyed or falls down. The question is if other blocks remain stable or also fall down?



(a) (b)

Figure 6: Vertical Impact: hitting o_1 causes o_1, o_3, o_4, o_5, o_6 falling down.

Our algorithm for Vertical Impact with o_1 as an input will generate a list of objects that will fall down if o_1 falls (or becomes destroyed). The algorithm is presented in Algorithm 1 and works as follows. At first, for any object that is in relation $above$ with o_1, consider a set O_1 of all objects that are in relation $above^{\star}$ with o_1 and a set O_2 of objects for which there is some object in relation $above$ from a set O_1. In the example from Fig. 6, there is one object in relation $above$ with o_1, namely o_3, then $O_1 = \{o_3, o_4, o_5\}$ (marked with a blue spline) and $O_2 = \{o_2, o_6\}$. Next, we need to determine 3 points: p_1 – a leftmost connection point between objects from the sets O_1 and O_2, p_2 – a rightmost connection point between objects from the sets O_1 and O_2, $p_3 = center(\bigcup O_1)$ – a cumulated center of mass for objects from a set O_1. We reason that object o_2 (and objects that are in relation $above^{star}$ with o_2) falls iff p_3 is to the left of p_1 or to the right of p_2. In our example it is the case that $x(p_3) < x(p_1)$, so objects from the set O_1 will fall down, i.e. they are added to the list $fall$ and marked on Fig. 6 (b) with dashed crosses. In fact, it is not the end of the algorithm, because, there are still other objects that may fall down too. For every object from O_2 (without o_1) we recursively lunch Algorithm 2 which checks how the cumulated center of mass of a given block and all blocks that are in relation $above^{\star}$ with it but are not in $fall$ list is located. If it is to the left of the leftmost or to the right of the rightmost connection point then the object falls. Afterwards, we check recursively other objects that are under already considered block. In our case we need to check o_2 and o_6 – see Fig. 6 b). While o_2 remains table, o_6 will fall, since $x(p_3) > x(p_2)$. It is still not the end of the algorithm, because, we need to check all objects that are below o_2 and o_6 (marked with a blue spline), in this case just o_7 which obviously will remain stable. Finally, we lunch recursively Algorithm 2 for objects that are under o_1 but in our case there are no such objects. The output of the algorithm in a given example is a list of objects that fall, namely $fall = \{o_1, o_3, o_4, o_5, o_6\}$.

Algorithm 1 Vertical impact

Input: object o_1
  initialize list $fall$ with one element i.e. o_1
  for all $o_2 \mid above(o_2, o_1)$ **do**
    if $x(center(o_2 \cup \bigcup o_3 \mid above^{\star}(o_3, o_2)) \leq \min_{o_3 \mid above(o_2,o_3) \wedge o_3 \neq o_1} x(left\_p(o_2, o_3))$ **or** $x(center(o_2 \cup \bigcup o_3 \mid above^{\star}(o_3, o_2)) \geq \max_{o_3 \mid above(o_2,o_3) \wedge o_3 \neq o_1} x(left\_p(o_2, o_3))$ **then**
      add o_2 to $fall$
      for all $o_3 \mid above^{\star}(o_3, o_2)$ **do**
        add o_3 to $fall$
    for all $o_4 \mid \exists o_3((above^{\star}(o_3, o_2) \wedge above(o_3, o_4) \wedge o_4 \notin fall) \vee above(o_1, o_4))$ **do**
      $fall_2$ = output from Algorithm 2 with inputs: o_4, $fall$
      $fall = fall \cup fall_2$
Output: list $fall$ of objects falling if o_1 will fall

Algorithm 2 Recursive falling checking

Input: object o_1, list of falling objects $fall$
  if $x(center(o_1 \cup \bigcup o_2 | above^{\star}(o_2, o_1) \wedge o_2 \notin fall) \leq \min_{o_3 | above(o_1,o_3) \wedge o_3 \notin fall} x(left\_p(o_1, o_3))$ **or** $x(center(o_1 \cup \bigcup o_2 | above^{\star}(o_2, o_1) \wedge o_2 \notin fall) \geq \max_{o_3 | above(o_1,o_3) \wedge o_3 \notin fall} x(right\_p(o_1, o_1))$ **then**
    add o_1 to $fall$
  for all $o_2 \mid above(o_1, o_2) \wedge o_2 \notin fall$ **do**
    $fall_2$ = output from Algorithm 2 with inputs: o_2, $fall$
    $fall = fall \cup fall_2$
Output: updated list of falling objects $fall$

3.2 Horizontal Impact

The second method – called Horizontal Impact – enables to reason about force propagation between objects. Notice, that hitting an object o_1 with a bird, affects also on objects touching o_1. We will (naively) say that the force propagates to nearby blocks. As an example consider a situation presented on Fig. 7, where o_3 is directly hit by a bird with a force F_{o_3}. Horizontal Impact method will enable us to estimate (qualitatively) F_{o_3} force and determine how it propagates to nearby objects. At first, the force will be propagate to direct neighbours, i.e., o_1, o_4 and o_5. Afterwards the force will be propagate also to o_2 and o_6 and then also to o_7 but the propagation is not infinite and there will be no significant force affecting on o_8. Since the propagating force always decreases, we have established a minimal force F_{min}. If the estimated force is lower then the minimal level, force propagation is stopped – for details see Definition 13.

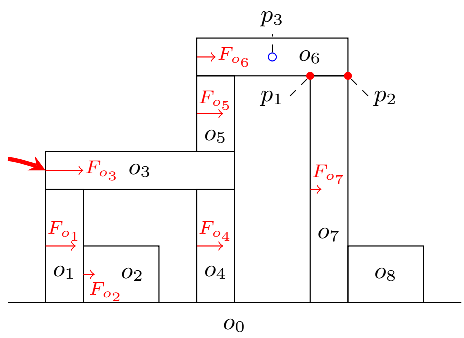


Figure 7: A Horizontal Impact method for determining force propagation after direct hitting o_3.

The first step in the Horizontal Impact method is to estimate the force (a value from interval [0,1]) affecting on a directly hit object – o_3 in our example. For simplicity, we have decided that the direct (horizontal) force depends only on the choice of trajectory - it is higher for the low trajectory. – see Definition 12.

Definition 12 (Direct force)**.**

$$\forall o_1 \in O, t \in T(F_{o_1}(o_1, t) = traj\_type(t, o_1))$$

and $traj\_type : T \times O \to [0, 1]$ is a following function:

$$\forall t \in T, \forall o_1 \in O(traj\_type(t, o_1) = \begin{cases} 1 & if\, t = traj_{\rightarrow}(o_1) \\ 0.7 & if\, t = traj_{\nearrow}(o_1) \end{cases}).$$

Afterwards, the force is propagated to objects that are in *touch* relation with a previous object. Consider object o_1 in *touch* relation with o_2 and force F_{o_1} affecting o_1 that propagates to F_{o_2} affecting o_2. The value of F_{o_2} force increases whenever F_{o_1} increases or the stability of o_1 decreases. Formally, propagated force is described in Definition 13.

Definition 13 (Propagated force)**.**

$$F_{o_2} = loc\_coeff \cdot F_{o_1} \cdot (1 - stability(o_1))^2,$$

where the loc_coeff distinguishes between the objects which are directly to the right of o_1, those that are directly above and those directly below. The propagated force is the highest in the first case ($loc\_coeff = 1$), smaller in the second case ($loc\_coeff = 0.8$) and even smaller in the last case ($loc\_coeff = 0.2$)

Notice that each force has a value from an interval [0,1]. After determining the force propagation we know what forces affect objects and therefore, we can investigate their effects. Namely, we can deduce, if a given force destroy an object o_1, knock it down or the object o_1 remains unmoved. The effect of the force is deduced just on the basis of the affected object mass, i.e. if $F_{o_1} \geq f_d(area(o_1) \cdot \rho(o_1))$ – the force is larger than a value of f_1 function of o_1 mass, then o_1 will be destroyed, otherwise if $F_{o_1} \geq f_f(area(o_1) \cdot \rho(o_1))$ then o_1 will be fall down, and otherwise o_1 remains unmoved, where $\forall a \in \mathbb{R}(f_d(a), f_f(a) \in [0,1] \wedge f_d(a) > f_f(a))$. Notice, that if $F_{o_1} \geq f_f(area(o_1) \cdot \rho(o_1))$ for some object o_1, then o_1 is destroyed or falls down. Hence, o_1 may have a vertical influence on other blocks and Vertical Impact algorithm presented in Section 3.1, namely Algorithm 1 with o_1 as an input needs to be lunched. As an example consider once more a situation from Fig. 7. Let's assume that o_3 is hardly hit with a bird and as a result, it influences significantly o_5 with a force F_{o_5} but o_3 itself remain unmoved. Let us assume now that $F_{o_5} \geq f_f(area(o_5) \cdot \rho(o_5))$ and as a result o_5 falls down. Therefore, we need to check if o_5 has a vertical impact on other blocks. As presented in Section 3.1, we need to check if the center of o_6 mass is between it's leftmost and rightmost connection points. In our case it is not, therefore we can conclude that o_6 will fall also. The algorithm does not stop in this moment but works as presented earlier in previous section in the Algorithm 2. The described algorithm for Horizontal Impact is presented in Algorithms 3 and 4.

Algorithm 3 Horizontal impact

Input: directly hit object o_i, fired bird b, trajectory t of a shot
 initialize an empty list $fall$ of falling objects
 initialize a list $forces$ of forces affecting objects, where $forces[k]$ indicates a force affecting o_k, i.e. F_{o_k}. Initially for each k, $forces[k] = 0$
 $forces[i] = traj\_type(t, o_i)$
 if $forces[i] \geq f_f(area(o_i) \cdot \rho(o_i))$ **then**
  add o_i to $fall$
 for all $o_j \mid touch(o_i, o_j)$ **do**
  $fall_2, force_2$ = output from Algorithm 4 with inputs:o_i, o_j, $fall$, $forces$
  $fall = fall_2$
  $forces = forces_2$
 for all $o_r \mid o_r \in fall$ **do**
  $fall_2$ = output from Algorithm 1 with input: o_r
  $fall_2 = fall \cup fall_2$
Output: list $fall$ of falling objects, list $forces$ of forces affecting objects

Algorithm 4 Recursive force propagation

Input: objects o_i, o_j, list $fall$ of falling objects, list $forces$ of forces affecting objects
 if $forces[i] \geq F_{min}$ **then**
  $forces[j] = forces[i] \cdot loc\_coeff \cdot (1 - stability(o_i))^2$
  if $forces[j] \geq f_f(area(o_j) \cdot \rho(o_j))$ **then**
   add o_j to $fall$
  for all $o_k \mid touch(o_k, o_j) \wedge forces[k] == 0$ **do**
   $fall_2, force_2$ = output from Algorithm 4 with inputs: o_j, o_k, $forces$, $fall$
   $fall = fall_2$
   $forces = forces_2$
Output: updated list $fall$ of falling objects, updated list $forces$ of forces affecting objects

Afterwards, we determine am influence value of a directly hit object to another object according to a given bird and shot trajectory. More precisely, we introduce a function $influence : O \times O \times B \times T \to [0,1]$ presented in Definition 14.

Definition 14 ($influence$ function)**.**

$$\forall o_i, o_j \in O, b \in B, t \in T(influence(o_i, o_j, b, t) = \begin{cases} 1 & \textit{if } o_j \in fall \\ forces[j] & \textit{otherwise.} \end{cases})$$

where o_i is a directly hit object, i.e. an input to the Algorithm 3.

Obviously, $influence(o_1, o_2, b, t) = 0$ means that while shooting at o_1 with a bird b and trajectory t, o_1 has no influence on o_2, whereas $influence(o_1, o_2, b, t) = 1$ means that if o_1 will fall, than undoubtedly o_2 will fall also.

3.3 Value estimation

In order to choose the best shot in a given Angry Birds gameplay we need to estimate an overall value of available shots. This value depends on the type of the bird that will be lunched, type of the shooting trajectory (high or low parabola) and a block which is a direct target of the shot. More precisely, the value of a shot, i.e., the value of a function $value : B \times T \times O \to \mathbb{R}$ increases whenever the stability of a direct target of a shot decreases or the influence of a directly hit object on interesting objects increases, where interesting objects are pigs and their shelters. For the exact description see in Definition 15.

Definition 15 ($value$ function)**.**

$$value(b, t, o_1) = \frac{corr\_fact}{stability(o_1)} \cdot \sum_{o_2 \in O} ivalue(o_2) \cdot influence(o_1, o_2, b, t) + shape\_coeff \cdot shape\_value,$$

where $ivalue : O \to \mathbb{R}$ maps an object into its interesting value as follows:

$$\forall o_1 \in O(ivalue(o) = \begin{cases} 1 & \textit{if } o_1 \textit{ is a pig} \\ shelter\_val(o_1) & \textit{otherwise} \end{cases}),$$

and the $corr\_fact$ is takes different values depending on the combination of the type of the bird and the type of material of the given object. This factor takes into account the ability of certain birds to destroy certain blocks (for instance yellow bird is very prolific efficient against wooden blocks). For the exact values of $corr\_fact$ see the table below:

Table 1: All possible cases of adding qualitative distances.

$bird\_type$ \ $object\_type$	pig	ice	$wood$	$stone$
red	1	0.7	0.8	0.3
$blue$	1	1	0.1	0.01
$yellow$	1	0.1	1	0.01
$white$	1	0.7	0.8	0.6
$black$	1	1	1	1

Based on the fact that spheres play a significant role on certain game levels, we have decided to increase their value in the following way. If a sphere is located higher than some pig and there is a straight path (without any obstacles) leading from the sphere to that pig we increase the value of the sphere. We further increase the sphere's value for each additional pig on the given path. We only count one such path (the one with the most pigs on it's way). The $shape\_value$ returns the highest number of pigs on the path leading from the given sphere to any pig and $shape\_coeff$ $(= 0.4)$ scales down this number, so that it is still pays off better to shoot directly at a pig than to aim at a sphere that would kill that pig. The provided trajectory module enables to determine directly reachable objects. After calculating reachable objects, we indicate a best shot as a one with a highest value among reachable shots. Notice, that since we consider only shooting at center points of objects, the number of available and reachable shots is small enough to perform all presented calculations in a reasonable time.

4 Evaluation

We have tested our algorithm on the first twenty one levels of the Poached Eggs scenario. If the algorithm failed to complete a given level, we repeated that level, but only once. If it failed to complete a given level twice, we would move on to the next level. It took our algorithm 33 minutes to go through all the 21 levels. It failed to complete 2 levels. The total score recorded was 753080, which gives an average score of 35861 per level. We also run the Naïve Naive Agent under the same conditions. It took the Naïve Agent 34 minutes to go through all the levels. It failed to complete 3 levels. The total score recorded was 687490, which gives an average score of 32738 per level.

5 Conclusions and future work

We have outlined a procedure for reasoning about the choice of a target in an Angry Birds game. The procedure involves several notions, which are central to the reasoning, such as stability, shelter, impact, influence. We choose our target to be the object that has a low stability, but it influences (by having a high, either vertical or horizontal, impact) objects which are pigs or shelters of pigs. Further testing is required to fine-tune the coefficients used in formulas for calculating numerical values of these notions (for instance the density of building materials). The procedure shows promise, but it has its flaws. There are certain configurations of objects, which serve as counter-examples to our reasoning. However these configurations are mostly theoretical possibilities as they seldom occur in the actual game. Still there is a lot of work to be done in order to expand our reasoning as to include the abilities of certain birds (for instance the ability to drop an egg of the white bird) and to include the behaviour of blocks of certain shapes (spheres or certain complex polygons). There is also potential for extending the procedure to specify how and where a given block will fall if it falls. In other words one can use the above-mentioned concepts to reason not only that a given block will fall but that it will fall, say, to the right and hit another block. All of this can be done using the introduced notion of connection points.

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