

Transposition Table, History Heuristic, and other Search Enhancements

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Abstract

- Introduce heuristics to improve the efficiency of alpha-beta based searching algorithms.
 - Re-using information: Transposition table.
 - ▷ *Can also be used in MCTS based searching.*
 - Adaptive searching window size.
 - Better move ordering.
 - Dynamically adjusting the searching depth.
 - ▷ *Decreasing*
 - ▷ *Increasing*
- Study the effect of combining multiple heuristics.
 - Each enhancement should not be taken in isolation.
 - Try to find a combination that provides the greatest reduction in tree size.
- Be careful on the type of game trees that you do experiments on.
 - Artificial game trees.
 - Depth, width and leaf-node evaluation time.
 - A heuristic that is good on the current experiment setup may not be good some years in the future because of the the game tree can be evaluated much deeper in the the same time using faster CPU's.

Enhancements and heuristics

- **Always used enhancements**
 - Alpha-beta, NegaScout or Monte-Carlo search based algorithms
 - Iterative deepening
 - Transposition table
- **Frequently used heuristics**
 - Knowledge heuristic: using domain knowledge to enhance the design of evaluation functions or to make the move ordering better.
 - Aspiration search
 - Refutation tables
 - Killer heuristic
 - History heuristic
- **Some techniques about aggressive forward pruning**
 - Null move pruning
 - Late move reduction
- **Search depth extension**
 - Conditional depth extension: to check doubtful positions.
 - Quiescent search: to check forceful variations.

Transposition tables

- We are searching a game graph, not a game tree.
 - Interior nodes of game trees are not necessarily distinct.
 - It may be possible to reach the same position by more than one path.
 - ▷ *Save information obtained from searching into a **transposition table**.*
 - ▷ *When being to search a position, first check whether it has been searched before or not.*
 - ▷ *If yes, reuse the information **wisely**.*
- Several search engines, such as NegaScout, need to re-search the same node more than once.
- How to use information in the transposition table?
 - Assume the position p has been searched before with a depth limit d' and the result is stored in a table.
 - Suppose p is to be searched again with the depth limit d .
 - If $d' \geq d$, then no need to search anymore.
 - ▷ *Just retrieve the result from the table.*
 - If $d' < d$, then use the best move stored as the starting point for searching.
- **Need to be able to locate p in the transposition table, which is large, efficiently.**

Transposition tables: contents

- What are recorded in an entry of a **transposition table**?
 - The position p .
 - ▷ *Note: the position also tells who the next player is.*
 - Searched depth d .
 - Best value in this subtree of depth d .
 - ▷ *Can be an exact value when the best value is found.*
 - ▷ *Maybe a value that causes a cutoff.*
 - *In a MAX node, it says at least v when a beta cut off occurred.*
 - *In a MIN node, it says at most v when an alpha cut off occurred.*
 - Best move, or the move caused a cut off, for this position.

Transposition tables: updating rules

- It is usually the case that at most one entry of information for a position is kept in the transposition table.
- When it is decided that we need to record information about a position p into the transposition table, we may need to consider the followings.
 - If p is not currently recorded, then just store it into the transposition table.
 - ▷ *Be aware of the fact that p 's information may be stored in a place that previously occupied by another position q and $p \neq q$.*
 - ▷ *In most cases, we simply overwrite.*
 - If p is currently recorded in the transposition table, then we need a good **updating rule**.
 - ▷ *Some programs simply overwrite with the latest information.*
 - ▷ *Some programs compare the depth, and use the one with a deeper searching depth.*
 - *When the searching depths are the same, one normally favors one with the latest information.*

Alpha-beta (Mini-Max) with memory

- **Algorithm $F4.1'$** (position p , value $alpha$, value $beta$, integer $depth$) // **MAX node**
 - check whether a value of p has been recorded in the transposition table
 - if yes, then HASH HITS with value m' , flag $exact$ and depth $depth'$!!
 - ...
- begin
 - ▷ $m := -\infty$ or m' if HASH HITS with an exact value /* m is the current best lower bound; fail soft */
 - ▷ ...
 - ▷ if $m \geq beta$ then {record the hash entry as a lower bound m ; return m } // beta cut off
 - ▷ for $i := 2$ to b do
 - ▷ ... recursive call
 - ▷ 14: if $m \geq beta$ then { record the hash entry as a lower bound m ; return m } // beta cut off
- end
- if $m > alpha$ then record the hash entry as an exact value m
- else record the hash entry as an upper bound m ;
- return m

Hash hit: discussions

- Be careful to check whether the position is exactly the same.
 - The turn or who the current player is is crucial in deciding whether the position is exactly the same.
 - To make it easy, usually positions to be played by different players are stored in different tables.
- The recorded entry consists of 4 parts:
 - the value m' ;
 - the depth $depth'$ where it was recorded;
 - a 3-way flag *exact* indicating whether it is
 - ▷ an exact value;
 - ▷ a lower bound value causing a beta cut; or
 - ▷ an upper bound value causing an alpha cut;
 - the child where m' comes from or causing a cut to happen.

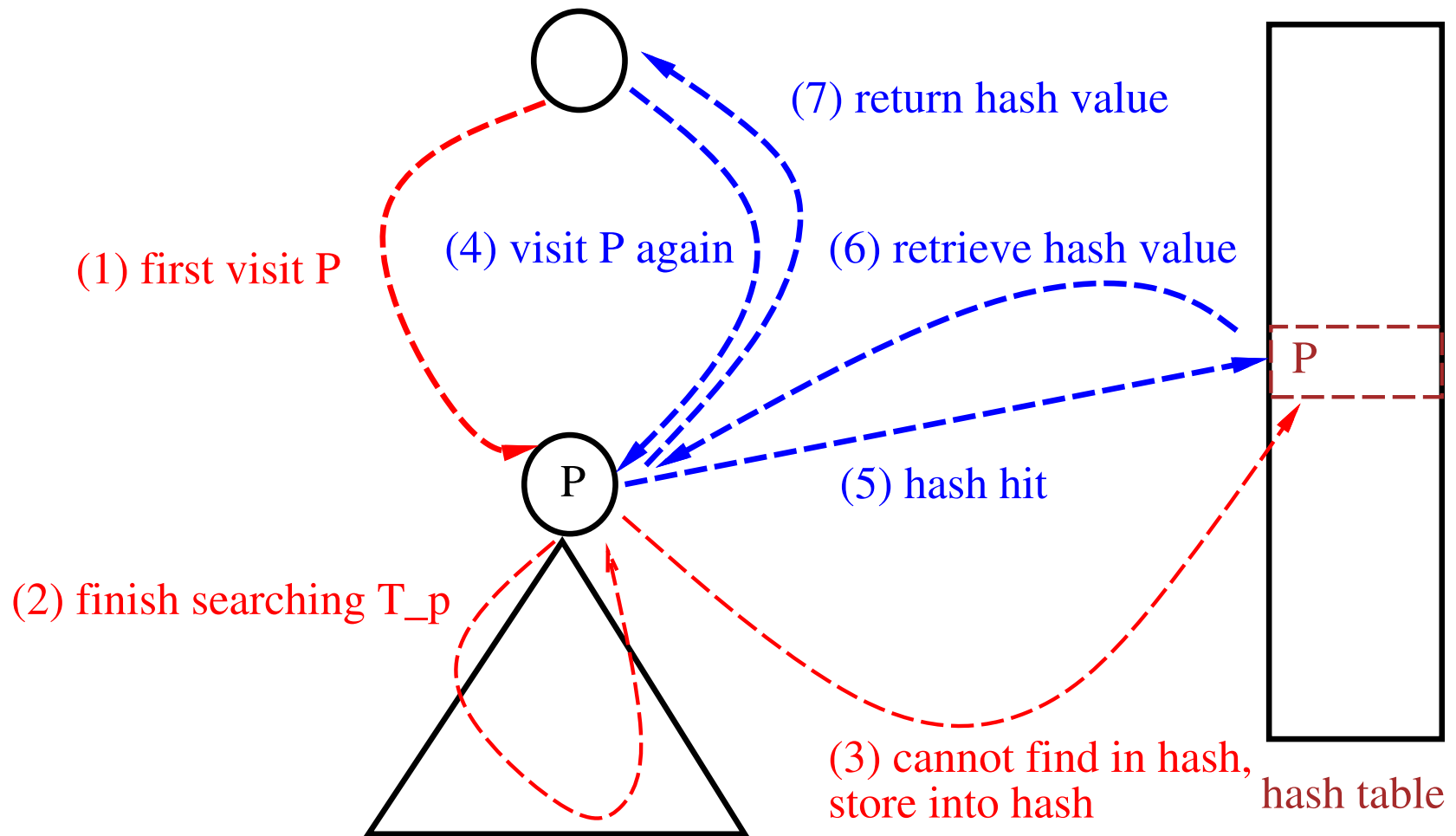
Hash hit: code

- If $depth' < depth$, namely, we have searched the tree shallower before, then **normally**
 - ▷ if it is an exact value, use m' as the initial value for searching;
 - ▷ if it is a bound, do not use m' at all.
- If $depth' \geq depth$, namely, we have searched the tree **not shallower** before.
 - It is an exact value.
 - ▷ Immediately return m' as the search result.
 - It is a lower bound.
 - ▷ Raise the alpha value by
$$alpha = \max\{alpha, m'\}$$
 - ▷ Check whether this causes a beta cut!
 - It is an upper bound.
 - ▷ Lower the beta value by
$$beta = \min\{beta, m'\}$$
 - ▷ Check whether this causes an alpha cut!

Hash hit: comments

- The above code $F4.1'$ is the code for the MAX node.
 - Need to write similarly for the MIN node $G4.1'$.
 - Need to take care of the NegaMAX version $F4.1$.
- Reasons you need to make “turn” into the hash design.
 - Sometimes, it is possible a legal arrangement of pieces on the board can be reached by both players.
 - ▷ *In Chinese dark chess, when a cannon captured an opponent, it can travel to a cell whose Manhattan distance is even in one ply.*
 - When you do null move pruning (see later slides for details).

Hash hit: Illustration



Zobrist's hash function

- Find a hash function $hash(p)$ so that with a very high probability that two distinct positions are mapped into distinct locations in the table.
- Using **XOR** to achieve fast computation.
- Properties of XOR used:
 - associativity: $x \text{ XOR } (y \text{ XOR } z) = (x \text{ XOR } y) \text{ XOR } z$
 - commutativity: $x \text{ XOR } y = y \text{ XOR } x$
 - $x \text{ XOR } x = 0$
 - ▷ $x \text{ XOR } 0 = x$
 - ▷ $(x \text{ XOR } y) \text{ XOR } y = x \text{ XOR } (y \text{ XOR } y) = x \text{ XOR } 0 = x$
 - $x \text{ XOR } y$ is **uniformly random** if x and y are also uniformly random
 - ▷ A binary string is uniformly random if each bit has an equal chance of being 0 and 1.
 - ▷ Not all operators, such as OR and AND, can preserve uniform randomness.

Hash function: design

- Assume there are k different pieces and each piece can be placed into r different locations in a 2-player game with red and black players.
 - Obtain $k \cdot r$ random numbers in the form of $s[*piece*][*location*]$
 - Obtain another 2 random numbers called $color[red]$ and $color[blk]$.
- Given a position p with $next$ being the color of the next player that has x pieces where q_i is the i th piece and l_i is the location of q_i .
 - $hash(p) = color[next] \text{ XOR } s[q_1][l_1] \text{ XOR } \dots \text{ XOR } s[q_x][l_x]$
- Comment: can be extended to games with arbitrary number of players, and kinds of and number of pieces.
- We can also remove $color[next]$ from the hash design and maintain 2 hash tables, one for each player.

Hash function: update

- $hash(p)$ can be computed **incrementally**.
 - A new piece q_{x+1} is placed at location l_{x+1} , then
 - ▷ $new\ hash\ value = hash(p) \text{ XOR } s[q_{x+1}][l_{x+1}]$.
 - A piece q_y is removed from location l_y , then
 - ▷ $new\ hash\ value = hash(p) \text{ XOR } s[q_y][l_y]$.
 - A piece q_y is moved from location l_y to location l'_y then
 - ▷ $new\ hash\ value = hash(p) \text{ XOR } s[q_y][l_y] \text{ XOR } s[q_y][l'_y]$.
 - A piece q_y is moved from location l_y to location l'_y and **captures** the piece q'_y at l'_y then
 - ▷ $new\ hash\ value = hash(p) \text{ XOR } s[q_y][l_y] \text{ XOR } s[q_y][l'_y] \text{ XOR } s[q'_y][l'_y]$.
 - Change the next player from $next$ to $\neg next$, then
 - ▷ $new\ hash\ value = hash(p) \text{ XOR } color[next] \text{ XOR } color[\neg next]$.
- **It is also easy to undo a move.**
- Can use the above primitives to assembly almost, if not all, game playing plys.

Practical issues

- Normally, design a hash table H of 2^n entries, but with a **longer** key length of $n + m$ bits.
 - That is, $color[next]$ and each $s[piece][location]$ are random values each of $n + m$ bits.
 - **Hash key** = $hash(p)$ is $n + m$ bits long.
 - **Hash index** = $hash(p) \bmod 2^n$.
 - Store the hash key to compare when there is a hash hit.
 - ▷ *Longer hash keys ensure better the chance of finding false positive entries.*
 - ▷ *Usually ≥ 64 bits.*
- How to store/update a hash entry?
 - Store it when the entry is empty.
 - Use a good updating rule to replace an old entry.
- How to match an entry?
 - First compute hash index $i = hash(p) \bmod 2^n$
 - Compare $hash(p)$ with the stored key in the i th entry $H[i].key$ to decide whether we have a hit.
 - Since the error rate is very small, if m is large enough, there is no need to store the exact position in making a comparison.

Clustering of errors

■ Errors

- Hash collision

- ▷ *Two distinct positions store in the same hash entry.*

- Hash clash

- ▷ *Two distinct positions have the same hash key.*

■ Though the hash codes are uniformly distributed, the idiosyncrasies of a particular problem may produce an unusual number of clashes.

- if $hash(p^*) = hash(p^+)$, then

- ▷ *adding the same pieces at the same locations to positions p^* and p^+ produce the same clashes;*

- ▷ *removing the same pieces at the same locations from positions p^* and p^+ produce the same clashes.*

Error rates

■ Estimation of the error rate:

- Assume this hash function is uniformly distributed.
- The chance of error for hash clash is $\frac{1}{2^{n+m}}$.
- Assume during searching, 2^w nodes are visited.
- The chance of no clash in these 2^w visits is

$$P = \left(1 - \frac{1}{2^{n+m}}\right)^{2^w} \simeq \left(\frac{1}{e}\right)^{2^{-(n+m-w)}}.$$

- ▷ When $n + m - w$ is 5, $P \simeq 0.96924$.
- ▷ When $n + m - w$ is 10, $P \simeq 0.99901$.
- ▷ When $n + m - w$ is 20, $P \simeq 0.99999904632613834096$.
- ▷ When $n + m - w$ is 32, $P \simeq 0.99999999976716935638$.

● Currently (2018):

- ▷ $n + m = 128$ or at least 64
- ▷ $n \leq 32$
- ▷ $w \leq 34$

Comments

- A very good technique that is used in many applications including most game playing codes even the ones based on Monte-Carlo search engines.
- A must have when you want to efficiently find patterns that change incrementally.
- Can be used in many other applications.

Intuitions for possible enhancements

- **The size of the search tree built by a depth-first alpha-beta search largely depends on the order in which branches are considered at interior nodes.**
 - It looks good if one can search the best possible subtree first in each interior node.
 - A better move ordering normally means a better way to prune a tree using alpha-beta search.
- **Enhancements to the alpha-beta search have been proposed based on one or more of the following principles:**
 - knowledge;
 - window size;
 - better move ordering;
 - forward pruning;
 - dynamic search extension;
 - ...

Knowledge heuristic

- Use game domain specified knowledge to obtain a good
 - move ordering;
 - evaluating function.
- Moves that are normally considered good for chess like games:
 - Moves to avoid being checking or captured
 - Checking moves
 - Capturing moves
 - ▷ *Favor capturing pieces of important.*
 - ▷ *Favor capturing pieces using pieces as little as possible.*
 - Moving of pieces with large material values
- Search good moves first can find the best move easier and earlier.
 - This is also a must have technique.

Aspiration search

- It is seldom the case that you can greatly increase or reduce your chance of winning by playing only one or two plys.
- The normal alpha-beta search usually starts with a $(-\infty, \infty)$ search window.
- If some idea of the range of the search will fall is available, then tighter bounds can be placed on the initial window.
 - The tighter the bound, the faster the search.
 - Some possible guesses:
 - ▷ *During iterative deepening, assume the previous best value is x , then use $(x - threshold, x + threshold)$ as the initial window size where $threshold$ is a small value.*
- If the value falls within the window then the original window is adequate.
- Otherwise, one must re-search with a wider window depending on whether it fails high or fails low.
- Reported to be at least 15% faster than the original alpha-beta search [Schaeffer '89].

Aspiration search — Algorithm

- Iterative deepening with aspiration search.
 - p is the current board
 - $limit$ is the limit of searching depth, assume $limit > 3$
 - $threshold$ is the initial window size
- Algorithm IDAS($p, limit, threshold$)
 - $best := F4(p, -\infty, +\infty, 3)$ // initial value
 - $current_depth_limit := 4$
 - while $current_depth_limit \leq limit$ do
 - ▷ $m := F4(p, best - threshold, best + threshold, current_depth_limit)$
 - ▷ if $m \leq best - threshold$ then // failed-low
 - $m := F4(p, -\infty, m, current_depth_limit)$
 - ▷ else if $m \geq best + threshold$ then // failed-high
 - $m := F4(p, m, \infty, current_depth_limit)$
 - ▷ endif
 - ▷ endif
 - ▷ $best := m$ // found
 - ▷ if remaining time cannot do another deeper search then return $best$
 - ▷ $current_depth_limit := current_depth_limit + 1$
 - return $best$

IDAS: comments

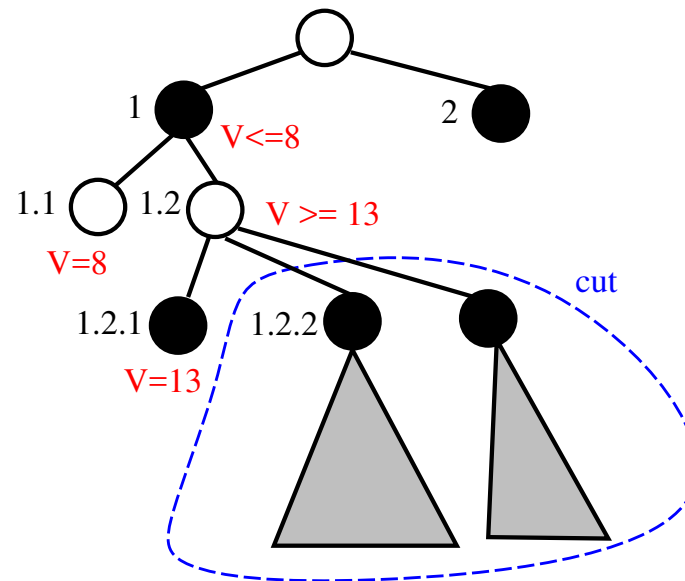
- **May want to try incrementally reshaping of window sizes.**
 - For example: try $[best - t_1, best + t_1]$ first.
 - If failed low, try $[best - t_1 - t_2, best - t_1]$.
 - If failed high, try $[best + t_1, best + t_1 + t_2]$.
 - ...
 - Need to decide various t_i via experiments.
- **Aspiration search is better to be used together with a transposition table so that information from the previous search can be reused later.**
- **Ideas here may also be helpful in designing better progressive pruning policy for Monte-Carlo based search.**
- **Takes a tiny effort to implement.**

Better move ordering

- **Intuition: the game evolves continuously.**
 - What are considered good or bad in previous plys cannot be off too much in this ply.
 - If iterative deepening or aspiration search is used, then what are considered good or bad in the previous iteration cannot be off too much at this iteration.
- **Techniques:**
 - Refutation table.
 - Killer heuristic.
 - History heuristic.

What moves are good?

- In alpha-beta search, a **sufficient**, or good, move at an interior node is defined as
 - one causes a cutoff, or
 - ▷ *Remark: this move is potentially good for its parent, though a cutoff happens may depend on the values of its older siblings.*
 - if no cutoff occurs, the one yielding the best minimax score, or
 - the one that is a sibling of the chosen yielding the best minimax score and has the same best score.



PV path

- For each iteration, the search yields a path for each move from the root to a leaf node that results in either the correct minimax value or an upper bound on its value.
 - This path is often called **principle variation (PV)** or **principle continuation**.
- Q: What moves are considered good in the context of Monte-Carlo simulation?
 - Can information in Monte-Carlo search accumulated in the previous plies be used in searching this ply?

Refutation tables

- Assume using iterative deepening with an increasing $current_depth_limit$ being bounded by $limit$.
 - Store the current best principle variation at $P_{current_depth_limit,i}$ for each depth i at the current depth limit $current_depth_limit$.
- The PV path from the $current_depth_limit = d-1$ ply search can be used as the basis for the search to $current_depth_limit = d$ ply at the same depth.
- Searching the previous iteration's path or **refutation** for a move as the initial path examined for the current iteration will prove sufficient to refute the move one ply deeper.
 - When searching a new node at depth i for the current depth limit $current_depth_limit$,
 - ▷ try the move made by this player at $P_{current_depth_limit-1,i}$ first;
 - ▷ then try moves made by this player at $P_{current_depth_limit-2,i}$;
 - ▷ ...

How to store the PV path

- **Algorithm $F4.2'$** (position p , value $alpha$, value $beta$, integer $depth$)
 - determine the successor positions p_1, \dots, p_b
 - if $b = 0$ // **a terminal node**
 - ...
 - then return $f(p)$ else begin
 - ▷ $m := -\infty$ // **m is the current best lower bound; fail soft**
 - $m := \max\{m, G4.2'(p_1, alpha, beta, depth - 1)\}$ // **the first branch**
 - $PV[current_depth_limit, depth] := p_1;$
 - if $m \geq beta$ then return(m) // **beta cut off**
 - ▷ for $i := 2$ to b do
 - ▷ 9: $\{t := G4.2'(p_i, m, m + 1, depth - 1)\}$ // **null window search**
 - ▷ 10: if $t > m$ then // **failed-high**
 - $\{PV[current_depth_limit, depth] := p_i;$
 - 11: if ($depth < 3$ or $t \geq beta$)
 - 12: then $m := t$
 - 13: else $m := G4.2'(p_i, t, beta, depth - 1)\}$ // **re-search**
 - ▷ 14: if $m \geq beta$ then return(m)} // **beta cut off**
 - end
 - return m

How to use the PV

- Use the PV information to do a better move ordering.
 - Assume the current depth limit from iteration deepening is *current_depth_limit*.
- Algorithm *F4.2.1'*(position p , value $alpha$, value $beta$, integer $depth$)
 - determine the successor positions p_1, \dots, p_b
 - // get a better move ordering by using information stored in PV
 - $k = 0$;
 - for $i = current_depth_limit - 1$ downto 1 do
 - if $PV[i, depth] = p_x$ and $d \geq x > k$, then
 - ▷ swap p_x and p_k ; // make this move the k th move to be considered
 - ▷ $k := k + 1$
 - ...

Killer heuristic

- A compact refutation table.
- Storing at each depth of search the moves which seem to be causing the most cutoffs, i.e., so called **killers**.
 - Currently, store two most recent cutoffs at this depth.
- The next time the same depth in the tree is reached, the killer move is retrieved and used, if valid in the current position.
- Comment:
 - It is plausible to record more than one killer move. However, the time to maintain them may be too much.
 - Most search engines now record **2** killer moves.

History heuristic

■ Intuition:

- A move M may be shown to be best in one position.
- Later on in the search tree a **similar** position may occur, perhaps only differing in the location of one piece.
 - ▷ *A position p and a position p' obtained from p by making one or two moves are likely to share important features.*
- Minor difference between p and p' may not change the position enough to alter move M from still being best.

■ Recall: In alpha-beta search, a **sufficient**, or good, move at an interior node is defined as

- one causes a cutoff, or
- if no cutoff occurs, the one yielding the best minimax score, or
- a move that is “equivalent” to the best move.

Implementation (1/2)

- Keep track of the **history** on what moves were good before.
 - Assume the board has q different locations.
 - Assume each time only a piece can be moved.
 - There are only q^2 possible moves.
 - Including more context information, e.g., the piece that is moved, does not significantly increase performance.
 - ▷ *If you carry the idea of including context to the extreme, the result is a transposition table.*
- The history table.
 - In each entry, use a counter to record the weight or chance that this entry becomes a good move during searching.
 - **Be careful: a possible counter overflow.**

Implementation (2/2)

- Each time when a move is good, increases its counter by a certain **weight**.
 - During move generation, pick one with the largest counter value.
 - ▷ *Need to access the history table and then sort the weights in the move queue.*
 - The deeper the subtree searched, the more reliable the minimax value is, except in pathological trees which are rarely seen in practice.
 - The longer the tree searched, and hence larger, the greater the differences between two arbitrary positions in the tree are, and less they may have in common.
 - By experiment: let $\text{weight} = 2^{\text{depth}}$, where *depth* is the depth of the subtree searched.
 - ▷ *Several other weights, such as 1 and depth, were tried and found to be experimentally inferior to 2^{depth} .*
- Killer heuristic is a special case of the history heuristic.
 - Killer heuristic only keeps track of one or two successful moves per depth of search.
 - History heuristic maintains good moves for all depths.
- History heuristic is very **dynamic**.

History heuristic: counter updating

- **Algorithm $F4.3'$** (position p , value $alpha$, value $beta$, integer $depth$)
 - determine the successor positions p_1, \dots, p_b
 - if $b = 0$ then return $f(p)$ else // **a terminal node**
 - begin
 - ▷ $m := -\infty$ // **m is the current best lower bound; fail soft**
 - $m := \max\{m, G4.3'(p_1, alpha, beta, depth - 1)\}$ // **the first branch where $:= 1$; // where is the child best comes from**
 - if $m \geq beta$ then { $HT[p_1] += weight$; return(m) } // **beta cut off**
 - ▷ for $i := 2$ to b do
 - ▷ **9:** $\{t := G4.3'(p_i, m, m + 1, depth - 1);$ // **null window search**
 - ▷ **10:** if $t > m$ then // **failed-high**
 - $\{where := i;$ // **where is the child best comes from**
 - 11:** if ($depth < 3$ or $t \geq beta$)
 - 12:** then $m := t$
 - 13:** else $m := G4.3'(p_i, t, beta, depth - 1)$ // **re-search**
 - ▷ **14:** if $m \geq beta$ then { $HT[p_i] += weight$; return(m) } } // **beta cut off**
 - end
 - $HT[p_{where}] += weight$;
 - return m

History heuristic: usage of the counter

- **Algorithm $F4.3.1'$** (position p , value $alpha$, value $beta$, integer $depth$)
 - determine the successor positions p_1, \dots, p_b
 - order the legal moves p_1, \dots, p_b according to their weights in $HT[]$
 - ...

Comments: better move ordering

- Need a good sorting routine in $F4.3.1'$ to order the legal moves according to their history values.
 - The number of possible moves is small.
 - ▷ *Better sorting methods are known for very small number of objects.*
- Need to take care of the case for the chance of a counter overflow.
 - Need to perform **counter aging** periodically.
 - ▷ *That is, discount the value of the current counter as the game goes.*
 - ▷ *This also makes sure that the counter value reflects the “current” situation better, and to make sure it won’t be overflowed.*
- Ideas here may also be helpful in designing a better node expansion policy for Monte-Carlo based search.

Experiments: Setup

- Try out all possible combinations of heuristics.
 - 6 parameters with 64 different combinations.
 - ▷ *Transposition table*
 - ▷ *Knowledge heuristic*
 - ▷ *Aspiration search*
 - ▷ *Refutation tables*
 - ▷ *Killer heuristic*
 - ▷ *History heuristic*
- Searching depth from 2 to 5 for all combinations.
 - Applying searching upto the depth of 6 to 8 when a combination showed significant reductions in search depth of 5.
- A total of 2000 VAX11/780 equivalent hours are spent to perform the experiments [Schaeffer '89].

Experiments: Results

■ Using a single parameter:

- ▷ *History heuristic performs well, but its efficiency appears to drop after depth 7.*
- ▷ *Knowledge heuristic adds an additional 5% time, but performs about the same with the history heuristic.*
- ▷ *The effectiveness of transposition tables increases with search depth.*
- ▷ *Refutation tables provide constant performance, regardless of depth, and appear to be worse than transposition tables.*
- ▷ *Aspiration and minimal window search provide small benefits.*

■ Using two parameters

- ▷ *Transposition tables plus history heuristic provide the best combination.*

■ Combining three or more heuristics do not provide extra benefits.

Comments

- **Combining two best heuristics may not give you the best.**
 - This conclusion is implementation and performance dependent.
- **Need to weight the amount of time spent in realizing a heuristic and the benefits it can bring.**
- **Need to be very careful in setting up the experiments.**

Dynamically adjusting searching depth

- **Aggressive forward pruning:** do not search branches that seem to have little chance of being the best **too deep**.
 - Null move pruning
 - Late move reduction
- **Search depth extension:** search a branch deeper if a side is in “danger” .
 - Conditional depth extension: to check doubtful positions.
 - Quiescent search: to check forceful variations.
- **Comments:**
 - Similar ideas are shared by MCTS search by spending less time in hopeless branches, and spending more time in hopeful branches.
 - Spend at least some time in seems hopeless branches.
 - Maybe possible to come out with a hybrid technique.

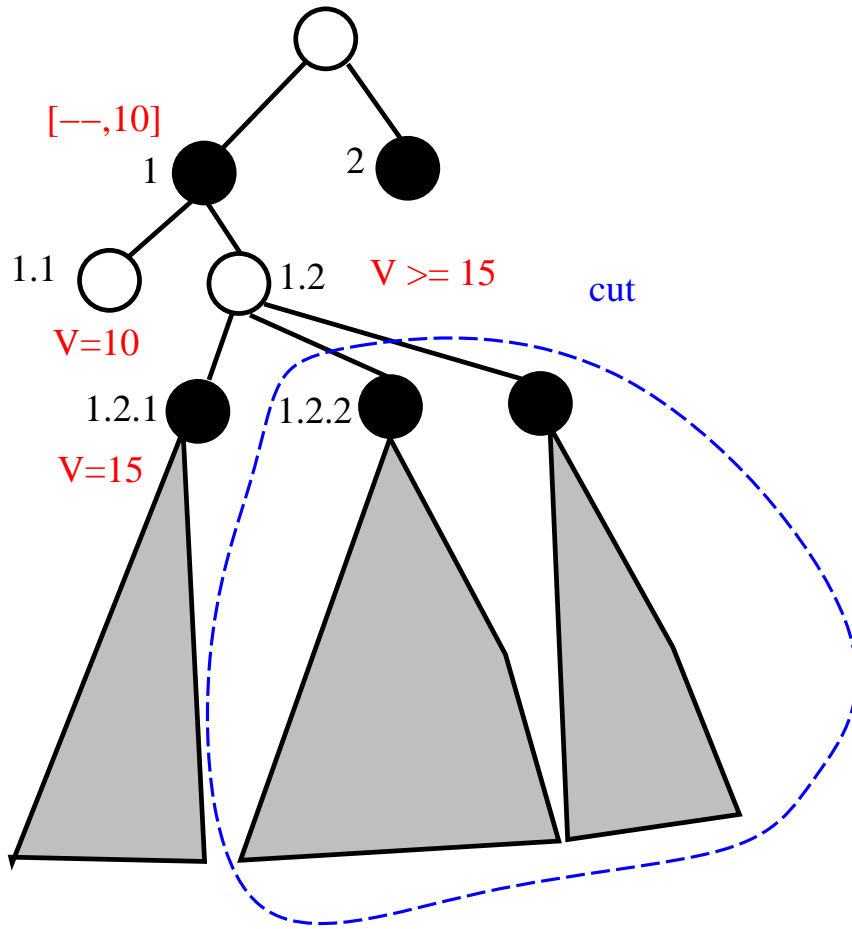
Null move pruning

- In general, if you forfeit the right to move and can still maintain the current advantage in a small number of plys, then it is usually true you can maintain the advantage in a larger number of plys.
- Algorithm:
 - It's your turn to move; the searching depth for this node is $depth$.
 - Make a null move, i.e., assume you do not move and let the opponent move again.
 - ▷ Perform an alpha-beta search with a reduced depth $depth - R$, where R is a constant decided by experiments.
 - ▷ If the returned value v is at least $beta$, then apply a beta cutoff and return v as the value.
 - ▷ If the returned value v does not produce a cutoff, then do the normal alpha-beta search.
- Similar ideas work for the case of your opponent's turn to move.

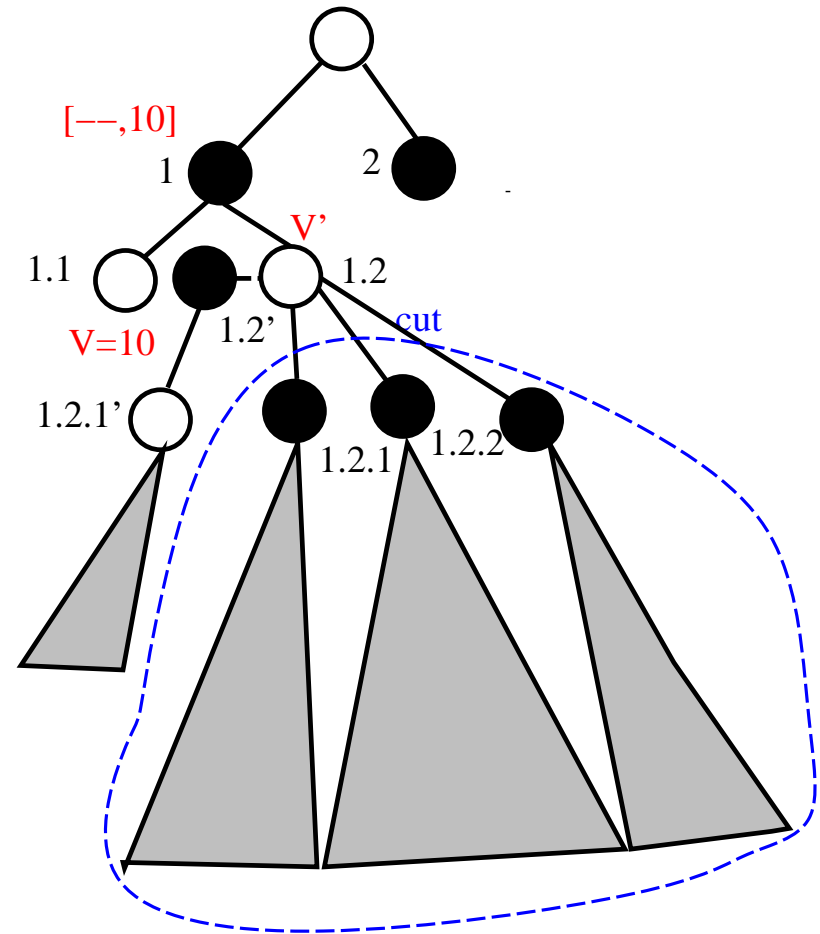
Null move pruning — Algorithm

- **Algorithm $F4.4'$** (position p , value $alpha$, value $beta$, integer $depth$, Boolean in_null)
 - determine the successor positions p_1, \dots, p_b
 - if $b = 0$ // **a terminal node**
 - ...
 - then return $f(p)$ else begin
 - ▷ If $depth \leq R + 3$ or in_null or dangerous, then goto Skip;
 - ▷ // **null move pruning**
 - ▷ $null_score := F4.4'(p', beta, beta + 1, depth - R - 1, TRUE)$ // p' is the position obtained by switching the player in p , and R is usually 2
 - ▷ if $null_score \geq beta$ return $null_score$ // **null move pruning**
 - ▷ Skip: // **normal NegaScout search**
 - ▷ $m := -\infty$ // m is the current best lower bound; fail soft
 - ▷ $m := \max\{m, G4.4'(p_1, alpha, beta, depth - 1, in_null)\}$
 - ▷ if $m \geq beta$ then return(m) // **beta cut off**
 - ▷ for $i := 2$ to b do
 - ▷ ...
- end
- return m

Null move pruning — Example



alpha-beta prune



null move prune

Null move pruning: analysis

■ Assumptions:

- The depth reduced, R , is usually 2 or 3.
- The disadvantage of doing a null move can offset the errors produced from doing a shallow search.
- Usually do not apply null move when
 - ▷ *your king is in danger, e.g., in check;*
 - ▷ *when the number of remaining pieces is small;*
 - ▷ *when there is a chance of Zugzwang;*
 - ▷ *when you are already in null move search, i.e., `in_null` flag is `TRUE`;*
 - ▷ *when the number of remaining depth is small.*

- Performance is usually good with about 10 to 30 % improvement, but needs to set the parameters right in order not to prune moves that need deeper search to find out their true values [Heinz '00].

Late move reduction (LMR)

■ Assumption:

- The move ordering is relatively good.

■ Observation:

- During search, the best move rarely comes from moves that are ordered very late in the move queue.

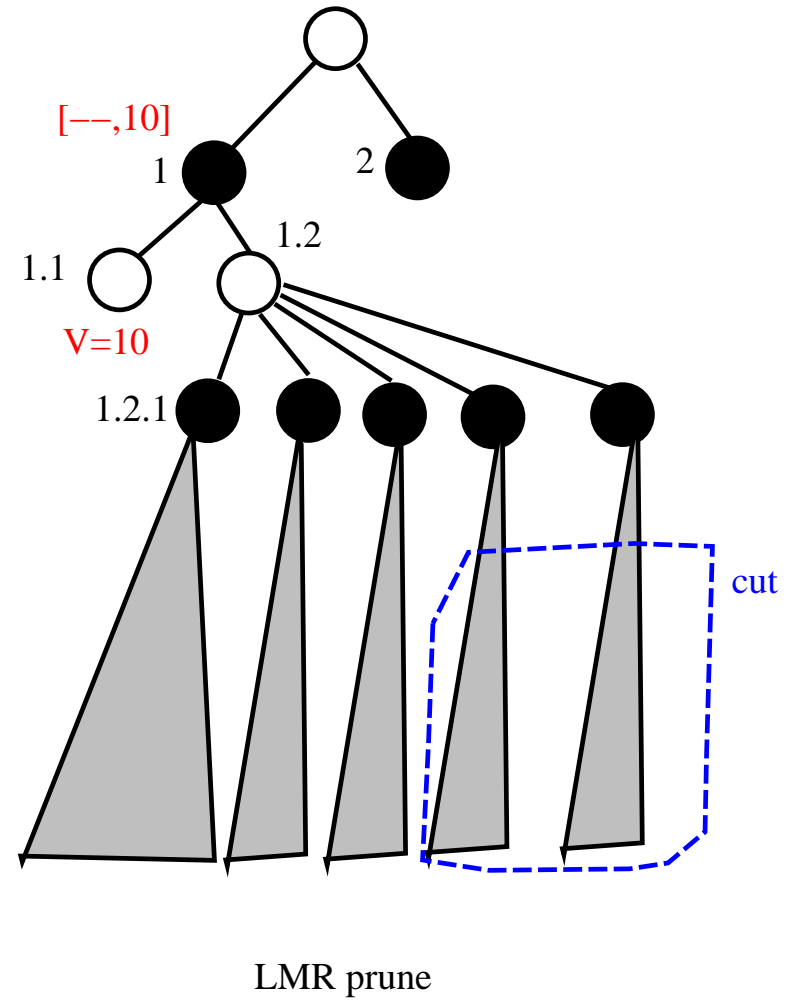
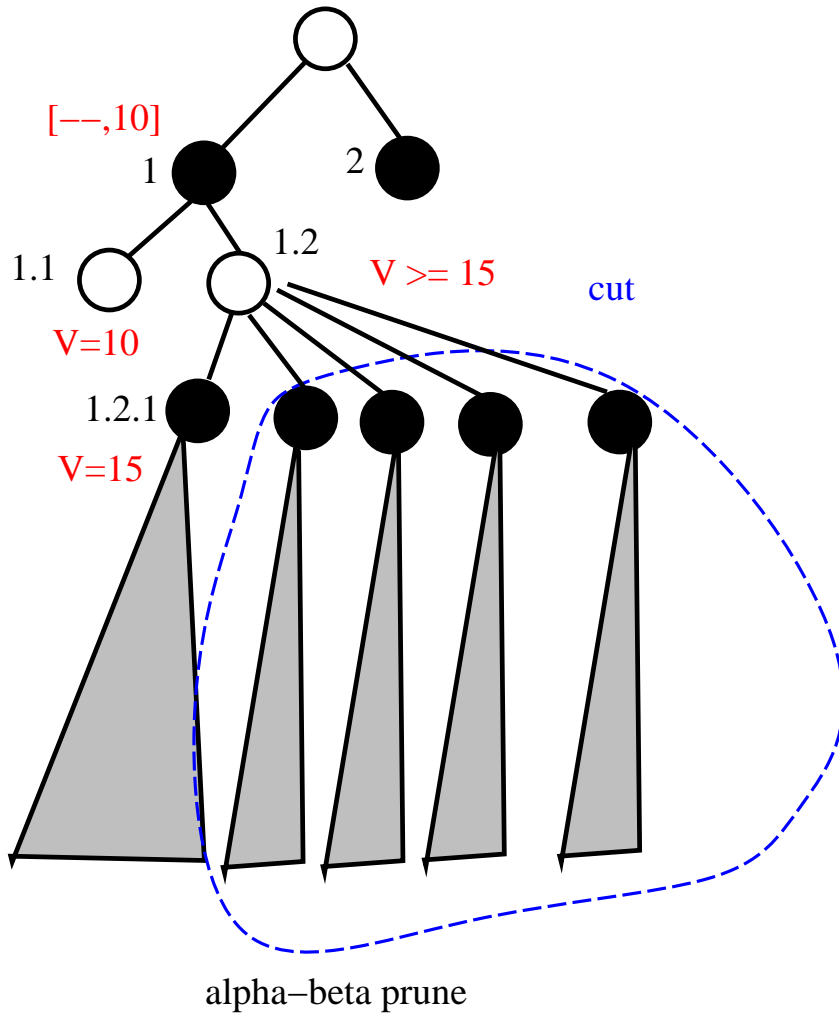
■ How to make use of the observation:

- If the first K , say $K = 3$ or 4 , moves considered do not produce a value that is better than the current best value, then
 - ▷ *consider reducing the depth of the rest of the moves with H , say $H = 3$.*
- If some moves considered with a reduced depth returns a value that is better than the current best, then
 - ▷ *re-search the game tree at a full depth.*

LMR — Algorithm

- **Algorithm $F4.5'$** (position p , value $alpha$, value $beta$, integer $depth$, Boolean in_lmr)
 - determine the successor positions p_1, \dots, p_b
 - if $b = 0$ // **a terminal node**
 - then return $f(p)$ else
begin
 - ▷ $m := -\infty$ // **m is the current best lower bound; fail soft**
...
 - ▷ for $i := 2$ to b do
 - ▷ if in_lmr or $i \leq K$ or $depth \leq H + 3$ or p_i is dangerous,
then { $depth' = depth$ $flag := in_lmr$;}
else { $depth' := depth - H$; $flag := true$ }; //**depth reduced**
 - ▷ 9: $t := G4.5'(p_i, m, m + 1, depth' - 1, flag)$ // **null window search**
 - ▷ 10: if $t > m$ then // **failed-high**
 - 11: if ($depth' < 3$ or $t \geq beta$)
 - 12: then $m := t$
 - 13: else $m := G4.5'(p_i, t, beta, depth - 1, in_lmr)$ // **re-search**
 - ▷ 14: if $m \geq beta$ then return(m) // **beta cut off**
 - end
 - return m

LMR — Example



LMR: analysis

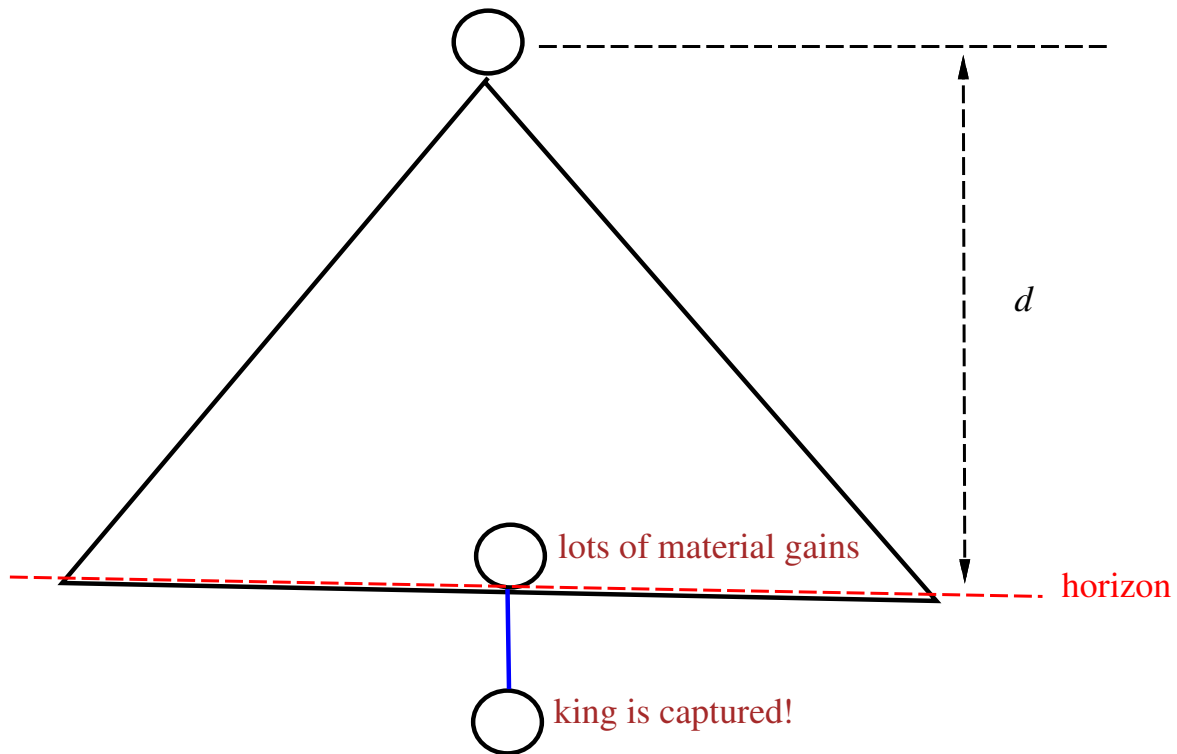
- Performance:
 - Reduce the **effective branching factor** to about 2.
 - ▷ *Effective branching factor is the average number of children considered in full details.*
- Usually do not apply this scheme when
 - your king is in danger, e.g., in check;
 - you or the opponent is making an attack;
 - the remaining searching depth is too small, say less than 3;
 - it is a node in the PV path.
- It is usually not a good idea to do this recursively, i.e., when *in_lmr* flag is true.

Dynamic search extension

■ Search extensions

- Some nodes need to be explored deeper than the others to avoid the **horizon effect**.
 - ▷ *Horizon effect is the situation that a stable value cannot be found because a fixed searching depth is set.*
- Needs to be very careful to avoid **non-terminating search**.
- Examples of conditions that need to extend the search depth.
 - ▷ *Extremely low mobility.*
 - ▷ *In-check.*
 - ▷ *Last move is capturing.*
 - ▷ *The current best score is much lower than the value of your last ply.*

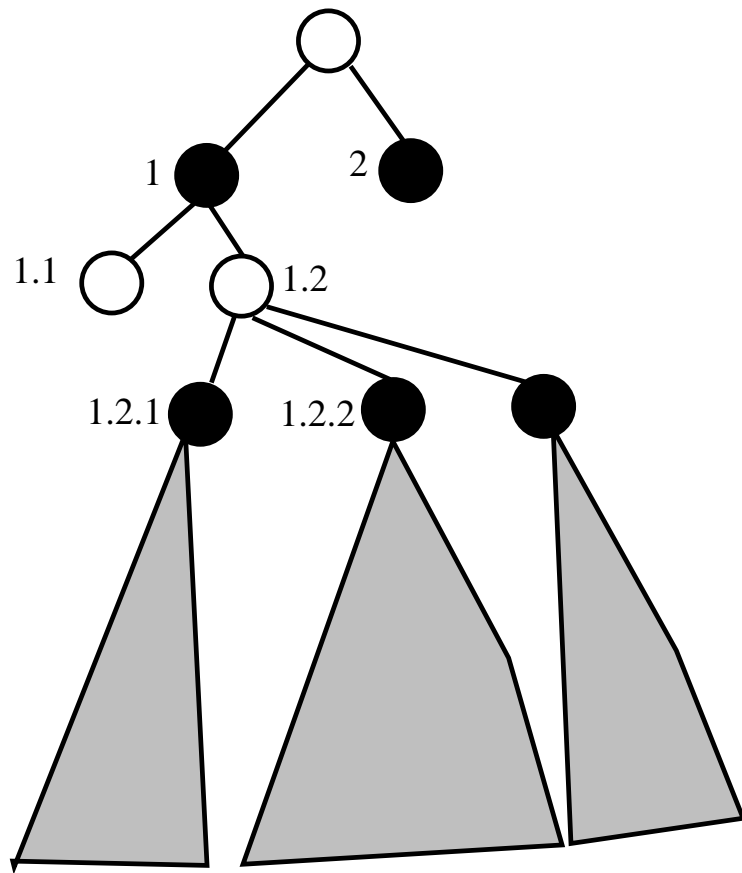
Horizon effect



Dynamic depth extension — Algorithm

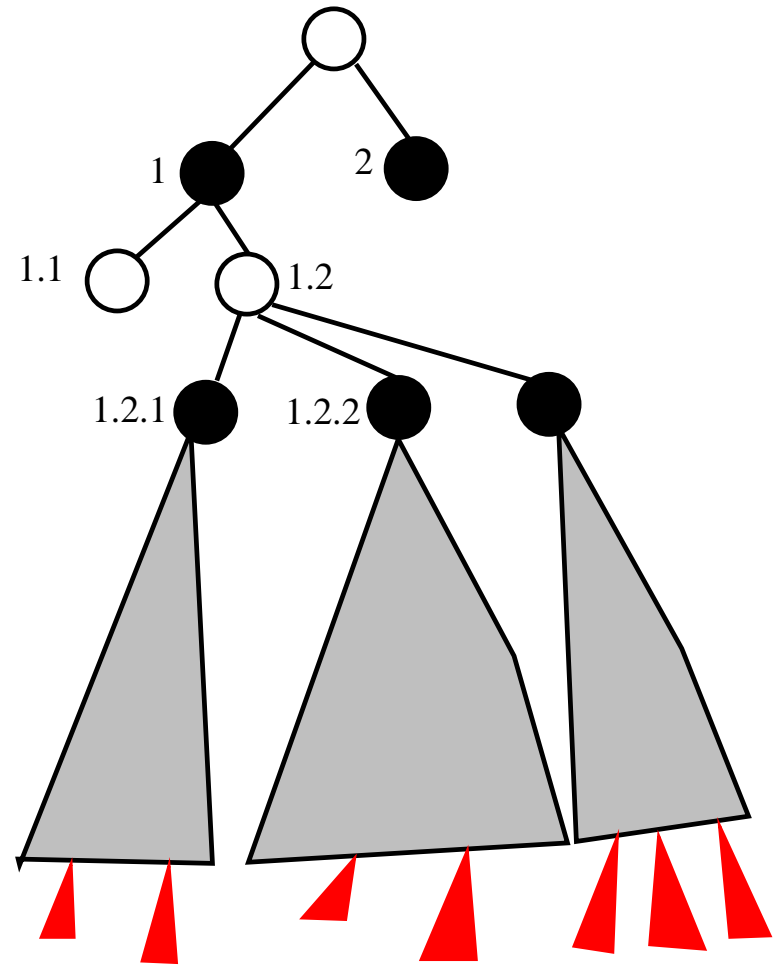
- **Algorithm $F4.6'$** (position p , value $alpha$, value $beta$, integer $depth$)
 - determine the successor positions p_1, \dots, p_b
 - if $b = 0$ // **a terminal node**
 - ...
 - then return $f(p)$ else begin
 - ▷ if p_1 is dangerous, then $depth' := depth + 1$ else $depth' := depth$
 - ▷ $m := -\infty$ // **m is the current best lower bound; fail soft**
 - $m := \max\{m, G4.6'(p_1, alpha, beta, depth' - 1)\}$ // **the first branch**
 - if $m \geq beta$ then return(m) // **beta cut off**
 - ▷ for $i := 2$ to b do
 - ▷ if p_i is dangerous, then $depth' := depth + 1$ else $depth' := depth$
 - ▷ 9: $t := G4.6'(p_i, m, m + 1, depth' - 1)$ // **null window search**
 - ▷ 10: if $t > m$ then // **failed-high**
 - 11: if ($depth < 3$ or $t \geq beta$)
 - 12: then $m := t$
 - 13: else $m := G4.6'(p_i, t, beta, depth' - 1)$ // **re-search**
 - ▷ 14: if $m \geq beta$ then return(m)} // **beta cut off**
 - end
 - return m

DSE — Illustration



normal search

search extension



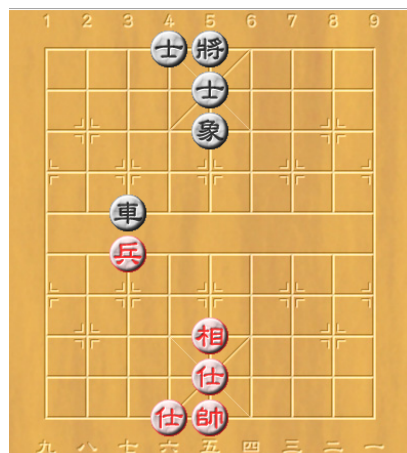
dynamic search extension

Quiescent search (1/2)

- **Quiescent search: to check further on **only** forceful variations.**
 - Invoke your search engine, e.g., alpha-beta search, to only consider moves that are in-check or capturing.
 - ▷ *May also consider checking moves.*
 - ▷ *May also consider allowing upto a fixed number, say 1, of non-capturing moves in a search path.*
 - Watch out of unneeded piece exchanges by checking the Static Exchange Evaluation (SEE) value first.

Quiescent search (2/2)

- We invoke a quiescent search so that searching is not stopped in the middle of a sequence of forced actions and counter-actions due to a fixed searching depth limit.
 - A sequence of checking and unchecking and finally leads to checkmate.
 - A sequence of moves with very limited number of choices.
 - A sequence of piece exchanges.
 - ▷ *It is p's turns to move, p will carry on the rest of exchanges only if he will be profitable.*
- Example: red pawn will capture black rook in red's turn, but black rook will not capture red pawn in black's turn.



Dynamic depth extension — Algorithm

- **Algorithm $F4.7'$** (position p , value $alpha$, value $beta$, integer $depth$)
 - determine the successor positions p_1, \dots, p_b
 - if $b = 0$ // **a terminal node**
 - ...
 - then return $Quiescent_F'(p, alpha, beta)$
 - else
 - begin
 - ▷ *continue to search*
 - ▷ ...
 - end
 - return m

Quiescent search algorithm

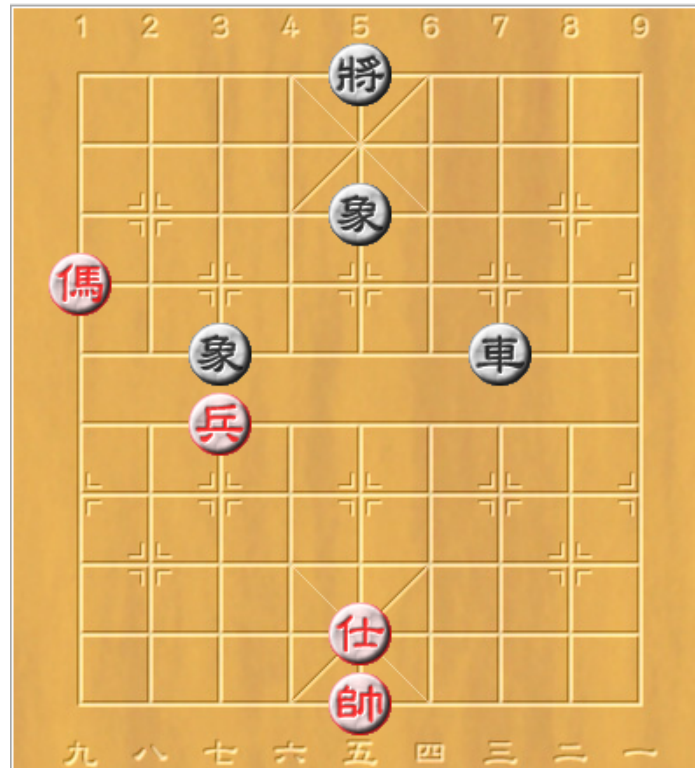
- **Algorithm** *Quiescent_F'*(**position** p , **value** $alpha$, **value** $beta$)
 - generate the successor positions $p_1, \dots, p_{b'}$ such that each p_i is either
 - ▷ capturing,
 - ▷ unchecking, or
 - ▷ checking // may add other types of non-quiescent moves
 - if $b' = 0$ then return $f(p)$ // a quiescent position
 - else $m := -\infty$
 - $quies := 0$; // count the number of quiescent capturing moves
 - for $i := 1$ to b' do
 - ▷ if p_i is not a capturing move OR $SEE(\text{destination}(p_i)) > 0$
then // not a quiescent position, search deeper
 - $\{m := \max\{m, \text{Quiescent}_G'(p_i, \max\{m, alpha\}, beta)\}$
 - if $m \geq beta$ then return (m) // beta cut off
 - else $quies := quies + 1$
 - if $quies = b'$ then return $f(p)$ // a quiescent position
else return m ;
- Can also use NegaScout as the main search engine.

Algorithm SEE(*location*)

- Assume w.l.o.g. it is red's turn and there is a black piece bp at *location*.
- Algorithm SEE(*location*)
 - $R :=$ the list of red pieces that can capture a black piece at *location*.
 - if $R = \emptyset$, then return 0;
 - Sort R according to their material values in non-decreasing order.
 - $B :=$ the list of black pieces that can capture a red piece at *location*.
 - Sort B according to their material values in non-decreasing order.
 - $gain := 0$; $piece := bp$;
 - While $R \neq \emptyset$ do
 - ▷ capture *piece* at *location* using the first element w in R ;
 - ▷ remove w from R ;
 - ▷ $gain := gain + value(piece)$;
 - ▷ $piece := w$;
 - ▷ if $B \neq \emptyset$
then { capture *piece* at *location* using the first element h in B ;
remove h from B ; $gain := gain - value(piece)$; $piece := h$; }
 - else break;
 - return $gain$ //the net gain of material values during the exchange

Example

- Net gain in red's turn.
 - Captured: two black elephants
 - Be captured: a red pawn and a red horse.
 - Usually, a pawn and a horse are more valuable than two elephants.
 - ▷ Hence this is a Quiescent position for the red side.

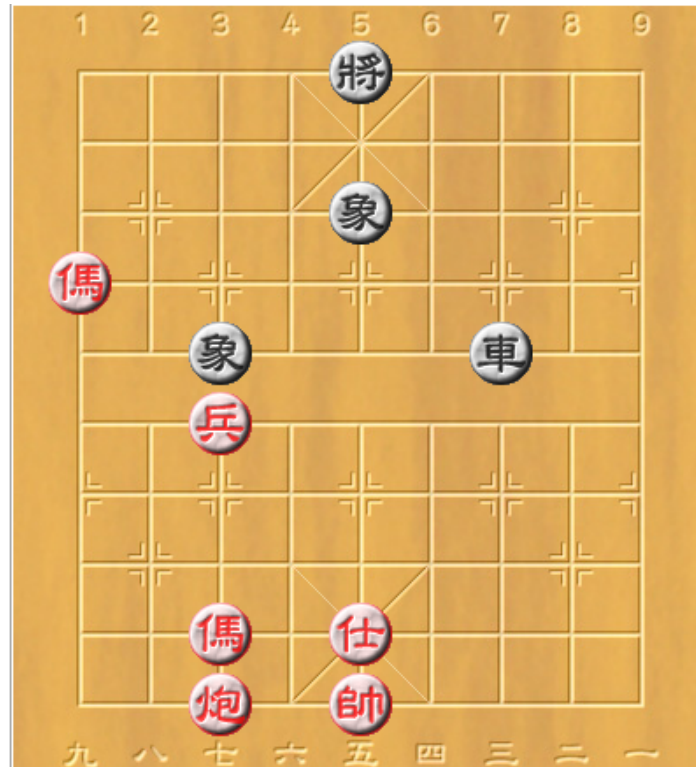


SEE: Comments

- We carry out a capturing move in Quiescent search only if the net gain is positive.
- Always use a lower valued piece to capture if there are two choices for getting the best gain.
- SEE is static and imprecise for performance issues.
 - Some pieces may capture or not able to capture a piece at a location because of the exchanges carried out before.
 - If SEE considers more dynamic situations, then it costs more time.

Counter example of SEE

- Red cannon can attack the location where the black elephant was at the river after red pawn captures black elephant, and then the black elephant captures the red pawn.
 - SEE advises RED not to initiate piece exchanges.
 - In this case, RED actually needs to do so.



Concluding comments

- There are many more such search enhancements.
 - Mainly designed for alpha-beta based searching.
 - It is worthy while to think whether techniques designed for one search method can be adopted to be used in the other search method.
- Finding the right coefficients, or parameters, for these techniques can only now be done by experiments.
 - Is there any general theory for finding these coefficients faster?
 - The coefficients need to be re-tuned once the searching behaviors change.
 - ▷ *Changing evaluation functions.*
 - ▷ *Faster hardware so that the searching depth is increased.*
 - ▷ ...
- Need to consider tradeoff between the time spent and the amount of improvements obtained.

References and further readings

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