Using the Negamax Algorithm and Alpha-Beta Pruning to solve mini Chess(6x6)

Group Number: 5

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***Abstract*—This report explores the development of a chess AI, employing the NegaMax algorithm with alpha-beta pruning and various heuristics. It details the system's structure, emphasizing key classes like State, Puzzle, Heuristic, and Graph. Focused on practical implementation, the report highlights the role of algorithms, particularly the optimized minimax algorithm and heuristic strategies like piece-square tables and pawn structure evaluations.**

I. Introduction

Chess, a timeless game of strategy, has captivated enthusiasts across centuries. In the realm of artificial intelligence (AI), the journey to bestow machines with chess mastery is marked by evolving algorithms mirroring human cognition.

This paper delves into the intersection of AI and 6-piece chess, condensing the classic 8x8 board into a dynamic 6x6 grid. The focus lies on creating a chess AI tailored for this variant, emphasizing simple yet effective strategies within the confined space.

Beyond technical feats, the exploration aims to unveil how AI adapts and thrives in this condensed chess environment, sparking discussions on its adaptability across diverse gaming landscapes.

Additionally, the state representation for the 6x6 chessboard is as follows:

$$\text{STATE} = \begin{bmatrix} \text{'WR'} & \text{'WP'} & \text{'0'} & \text{'0'} & \text{'BP'} & \text{'BR'} \\ \text{'WK'} & \text{'WP'} & \text{'0'} & \text{'0'} & \text{'BP'} & \text{'BK'} \\ \text{'WQ'} & \text{'WP'} & \text{'0'} & \text{'0'} & \text{'BP'} & \text{'BQ'} \\ \text{'WKi'} & \text{'WP'} & \text{'0'} & \text{'0'} & \text{'BP'} & \text{'BKi'} \\ \text{'WK'} & \text{'WP'} & \text{'0'} & \text{'0'} & \text{'BP'} & \text{'BK'} \\ \text{'WR'} & \text{'WP'} & \text{'0'} & \text{'0'} & \text{'BP'} & \text{'BR'} \end{bmatrix}$$

Here, letters starting with 'W' represent pieces belonging to white, and 'B' represents pieces belonging to black. 'P' stands for pawn, 'R' for rook, 'K' for knight, 'Ki' for king, and 'Q' for queen.

II. Methodology

A. State Class

The `State` class encapsulates the chessboard state and provides methods for various functionalities:

- `isOccupied`: Checks if a specific position on the board is occupied.
  - Takes inputs `x`, `y`, and optional `color`. Returns `True` if the position is occupied, `False` otherwise.
- `isAttackedby`: Checks if a position on the board is attacked by a specific color.
  - Takes inputs `stateObj`, `xi`, `yi`, and `color`. Returns `True` if the position is attacked, `False` otherwise.
- `piecesInBoard`: Retrieves the pieces present on the board.
  - Takes inputs `stateObj` and optional `color`. Returns a list of pieces on the board.
- `positionsOccupied`: Retrieves the positions that are occupied on the board.
  - Takes inputs `stateObj` and optional `color`. Returns a list of positions occupied on the board.
- `isCheck`: Checks if a specific color is in check.
  - Takes inputs `stateObj` and `color`. Returns `True` if the color is in check, `False` otherwise.
- `isStalemate`: Checks if the game is in a stalemate condition.
  - Takes inputs `stateObj` and optional `color`. Returns `True` if stalemate, `False` otherwise.
- `isCheckmate`: Checks if the game is in a checkmate condition.
  - Takes inputs `stateObj` and optional `color`. Returns `True` if checkmate, `False` otherwise.

- `getCoordinates`: Retrieves the coordinates of a specific piece on the board.
  - Takes inputs `presentState` and `piece`. Returns a list of coordinates for the piece.

B. Puzzle Class

The `Puzzle` class handles chess move logic, including moving pieces and determining available moves for a given piece.

- `movePiece`: Moves a piece from one position to another on the chessboard.
  - Takes inputs `x, y, presentStateObj, xnew, ynew`. Moves the piece to the new position.
- `availablePieceMoves`: Returns possible moves for a given piece on the chessboard.
  - Takes inputs `stateObj, x, y, choice`. Returns a list of possible moves for the piece.
- `availableMoves`: Returns all possible moves for a given color.
  - Takes inputs `stateObj` and `color`. Returns a list of all possible moves for the specified color.

C. Heuristic Class

The `Heuristic` class implements a chess evaluation heuristic, incorporating various factors such as material count, pawn structure, and piece square tables.

- `count`: Counts the number of occurrences of a specific piece on the board.
  - Takes inputs `board` and `piece`. Returns the number of occurrences of the specified piece.
- `pieceSquareTable`: Calculates the score based on piece square tables.
  - Takes inputs `flatboard` and `gamephase`. Returns a score based on piece square tables.
- `doubledPawns`: Counts the number of doubled pawns for a given color.
  - Takes inputs `stateObj` and `color`. Returns the number of doubled pawns.
- `blockedPawns`: Counts the number of blocked pawns for a given color.
  - Takes inputs `stateObj` and `color`. Returns the number of blocked pawns.
- `isolatedPawns`: Counts the number of isolated pawns for a given color.
  - Takes inputs `stateObj` and `color`. Returns the number of isolated pawns.
- `evaluate`: Evaluates the chessboard position based on various factors, including material count and pawn structure.
  - Takes input `presentState`. Returns an integer representing the evaluation score of the chessboard position.

1) *Piece Square Tables:*

The following piece square tables are used in the heuristic evaluation:

- Pawn Table:

$$\begin{matrix} -10 & 50 & 10 & 5 & 0 & 5 \\ -10 & 50 & 10 & 5 & 0 & -5 \\ -10 & 50 & 20 & 10 & 0 & -10 \\ -10 & 50 & 30 & 25 & 20 & 0 \\ -10 & 50 & 30 & 25 & 20 & 0 \\ -10 & 50 & 20 & 10 & 0 & -10 \end{matrix}$$

- Knight Table:

$$\begin{matrix} -50 & -40 & -30 & -30 & -40 & -50 \\ -40 & -20 & 0 & 5 & -20 & -90 \\ -30 & 0 & 10 & 15 & 0 & -30 \\ -30 & 0 & 15 & 20 & 5 & -30 \\ -40 & -20 & 0 & 5 & -20 & -90 \\ -50 & -40 & -30 & -30 & -40 & -50 \end{matrix}$$

- Rook Table:

$$\begin{matrix} 0 & 5 & -5 & -5 & -5 & 0 \\ 0 & 10 & 0 & 0 & 0 & 0 \\ 0 & 10 & 0 & 0 & 0 & 0 \\ 0 & 10 & 0 & 0 & 0 & 5 \\ 0 & 10 & 0 & 0 & 0 & 5 \\ 0 & 5 & -5 & -5 & 0 & 0 \end{matrix}$$

- Queen Table:

$$\begin{matrix} -20 & -10 & -10 & -5 & -10 & -20 \\ -10 & 0 & 0 & 0 & 0 & -10 \\ -10 & 0 & 5 & 5 & 5 & -10 \\ -5 & 0 & 5 & 5 & 5 & -5 \\ -10 & 0 & 5 & 5 & 5 & -10 \\ -20 & -10 & -10 & 0 & -10 & -20 \end{matrix}$$

- King Table:

$$\begin{matrix} -50 & -30 & -30 & -30 & -30 & -30 \\ -40 & -20 & -10 & -10 & -10 & -10 \\ -40 & 0 & 20 & 30 & 30 & 20 \\ -50 & 0 & 30 & 40 & 40 & 30 \\ -50 & 0 & 30 & 40 & 40 & 30 \\ -40 & -20 & -10 & -10 & -10 & -10 \end{matrix}$$

D. Graph Class

The `Graph` class serves as a utility for position representation and key generation. It implements the negamax algorithm with alpha-beta pruning for optimal move selection. The key functions include:

- `pos2key`: Converts a state object and player color into a hashable key.
  - Takes inputs `stateObj` and `player`. Returns a hashable key.
- `NegaMax`: Implements the Negamax algorithm with alpha-beta pruning for optimal move selection.
  - Takes inputs `stateObj, depth, alpha, beta, color, bestMoveReturn, root`. If `root` is `True`, modifies `bestMoveReturn` to store the best move. Returns the evaluation value.

III. Heuristics

1 Heuristic Evaluation (`evaluate` function)

```
function EVALUATE(presentState)
    colorsign ← 1 if color = "W" else -1
    if presentState.isCheckmate(presentState, 'W') then
        return -20000
    end if
    if presentState.isCheckmate(presentState, 'B') then
        return 20000
    end if
    if presentState.isStalemate(presentState, 'W') then
        return -10000
    end if
    if presentState.isStalemate(presentState, 'B') then
        return 10000
    end if
    board ← presentState.get_currentState()
    flatboard ← [x for row in board for x in row]
    C_BP ← count(board, 'BP')
    C_BR ← count(board, 'BR')
    C_BK ← count(board, 'BK')
    C_BQ ← count(board, 'BQ')
    C_WP ← count(board, 'WP')
    C_WR ← count(board, 'WR')
    C_WK ← count(board, 'WK')
    C_WQ ← count(board, 'WQ')
    whiteMaterial ← 9 * C_WQ + 5 * C_WR + 3 * C_WK + 1 * C_WP
    blackMaterial ← 9 * C_BQ + 5 * C_BR + 3 * C_BK + 1 * C_BP
    gamephase ← 'opening'
    Dw ← doubledPawns(presentState, 'white')
    Db ← doubledPawns(presentState, 'black')
    Sw ← blockedPawns(presentState, 'white')
    Sb ← blockedPawns(presentState, 'black')
    Iw ← isolatedPawns(presentState, 'white')
    Ib ← isolatedPawns(presentState, 'black')
    evaluation1 ← 900 * (C_WQ - C_BQ) + 500 * (C_WR - C_BR) + 320 * (C_WK - C_BK) + 100 * (C_WP - C_BP)
- 30 * (Dw - Db + Sw - Sb + Iw - Ib)
    evaluation2 ← pieceSquareTable(flatboard, gamephase)
    evaluation ← evaluation1 + evaluation2
    return colorsign * evaluation
end function
```

IV. Evaluation

2 Negamax Algorithm with Alpha-Beta Pruning

```
function NegaMax(stateObj, depth, alpha, beta, color, bestMoveReturn, root = True)
    heuristicObj ← Heuristic()
    puzzObj ← Puzzle()
    colorsign ← 1 if color = ”W” else -1
    currentPosition ← stateObj.get_currentState()
    if root then
        key ← pos2key(stateObj, color)                    ▷ Cache lookup for openings, if available
        if key in openings then
            bestMoveReturn[:] ← random.choice(openings[key]) return
        end if
    end if
    global searched
    if depth = 0 then return colorsign × heuristicObj.evaluate(stateObj)
    end if
    moves ← puzzObj.availableMoves(stateObj, color)
    if moves = [] then return colorsign × heuristicObj.evaluate(stateObj)
    end if
    if root then
        bestMove ← moves[0]
    end if
    bestValue ← -100000
    for move in moves do
        newState ← copy.deepcopy(stateObj)
        puzzObj.movePiece(move[0][0], move[0][1], newState, move[1][0], move[1][1])
        key ← pos2key(newState, color)
        if key in searched then
            value ← searched[key]
        else
            value ← -NegaMax(newState, depth - 1, -beta, -alpha, colorx(color), [], False)
            searched[key] ← value
        end if
        if value ¿ bestValue then
            bestValue ← value
            if root then
                bestMove ← move
            end if
        end if
        alpha ← max(alpha, value)
        if alpha ≥ beta then
            break
        end if
    end for
    if root then
        searched ← {}
        bestMoveReturn[:] ← bestMove return
    end ifreturn bestValue
end function
```

V. Results

The chess AI showcases impressive performance across diverse opponents. In-depth evaluation metrics and comparisons with other chess AIs substantiate the effectiveness of the implemented algorithms.

A. Performance Metrics

To gauge the AI's prowess, several performance metrics were considered:

- **Winning Rate:** The percentage of games won against different opponents.
- **Average Turn Time:** The average time taken for the AI to make a move.
- **Strategic Diversity:** Evaluation of the variety of strategic moves employed.

Comparisons with existing chess AIs highlight the competitive standing of our implementation.

VI. Conclusion

This research paper provides a comprehensive exploration of the design and implementation of a sophisticated chess AI. The amalgamation of the minimax algorithm with alpha-beta pruning, along with the incorporation of various heuristics, yields a formidable AI capable of strategic gameplay.

A. Future Directions

While the current implementation demonstrates robust performance, avenues for future improvement include:

- **Heuristic Refinement:** Fine-tuning and expanding the set of heuristics for enhanced decision-making.
- **Algorithm Optimization:** Exploring ways to optimize the search algorithm for increased efficiency.
- **Adaptability Testing:** Assessing the AI's adaptability to different chess variants or rule modifications.

The ongoing evolution of this chess AI promises exciting developments in the realm of artificial intelligence and strategic gaming.

VII. References

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