2024 Joint 13th International Conference on Soft Computing and Intelligent Systems and 25th International Symposium on Advanced Intelligent Systems (SCIS&ISIS) | 979-8-3503-7333-2/24/$31.00 ©2024 IEEE | DOI: 10.1109/SCISISIS61014.2024.10760135

Improving Prototype Intelligent Tactical Board for Rugby Sevens

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***Abstract*—In the last decade, advanced tactical understanding has become increasingly necessary for players and coaches in rugby, as has been the case in other team sports. Against this background, we have prototyped an intelligent tactical board tool for rugby sevens. This tool can compute a single normative offensive sequence derived from players' position and velocity information, consisting of running plays and hand-passing plays. The computed sequence serves as a reference for enhancing the tactical understanding of players and coaches. However, considering practical usage situations, displaying multiple offensive sequences is expected to be more suitable, as it provides a broader range of options. Yet, this is difficult to achieve due to the limitations of the simple branch and bound algorithm currently applied. Therefore, in this study, we enhance this prototype tool so that it can compute multiple normative offensive sequences. Moreover, to make the computed sequences more intuitively understandable, this study newly incorporates an integration function with a commercially available 3D visualization tool for rugby plays to this prototype tool. To confirm the functionality of the improved tool, we conduct a validation test using a real formation example from a video of an actual rugby sevens match.**

Keywords—sports information processing, rugby sevens, tactical board tool, offensive sequence computation, players' position and velocity information

I. INTRODUCTION

In the last decade, advanced tactical understanding has become increasingly crucial for players and coaches in rugby, as it has in other team sports. In particular, there is a growing importance in tactical understanding regarding plays that could lead to tries, as these are the primary source of scoring. Against this background, we have prototyped an intelligent tactical board tool for rugby sevens [1]. This prototype tool has a function to compute a single normative offensive sequence of running plays and hand-passing plays, which serves as a reference for enhancing the tactical understanding of players and coaches. The normative offensive sequence is derived from players' position and velocity information via the computation method previously proposed by us [2]–[4]. Furthermore, we have extended this prototype tool to allow users to set key ability parameters of players, such as maximum running speeds, hand-passing speeds, and hand-passing effective ranges [5], based on the actual abilities of players in both their own team and the opponent's team.

Although this prototype tool represents only one possible normative sequence, considering practical usage situations, displaying multiple normative offensive sequences is expected to be more suitable, as it provides a broader range of options, offering coaches and players enhanced flexibility and strategic depth in their decision-making processes. Furthermore, this prototype tool visualizes the offensive sequences from a top-down view using players' reachable areas [6] without any specific movements for other than ball carriers. This makes it difficult for players and coaches to intuitively understand the offensive sequences. Therefore, in this study, we enhance this prototype tool so that it can compute multiple normative offensive sequences. Moreover, for intuitive visualization of the offensive sequences, we implement an integration function with a commercially available 3D visualization tool for rugby plays [7] into this prototype tool. To confirm the functionality of the improved tool, we conduct a validation test using a real formation example from a video of an actual rugby sevens match.

II. RELATED WORK

Nowadays, numerous analytical methods, software, and devices are used for various team sports. Therefore, in this section, we describe only those closely related to this study.

Several studies have extensively explored data analysis in rugby [8]–[16]. Specifically, reference [8] evaluates dynamic pass networks to represent dynamic interactions between players. In [9], self-organizing maps that recognize relationships among team performance variables are used to visualize the game styles of teams. Reference [10] introduces a system to visually track the transition of tactical situations during a match, graphing traditional evaluation indicators (such as ball possession and area dominance) as well as a new indicator called 'initiative'. Reference [11] proposes a neural network-based method to predict binary outcomes of plays from play log data. In [12], supervised and unsupervised sequential pattern mining methods are compared based on the patterns they compute from play log data. In [13], six Expected Possession Value (EPV) models are constructed and compared using play log data to evaluate team offensive performance. Reference [14] models state-action value functions in Markov decision processes using play log data for evaluating player performance. Reference [15] applies a random forest model to player performance indicators to analyze the importance of each indicator. In [16], three pattern mining methods are applied to identify the best set of player movement patterns and to quantify the similarity among distinct patterns.

To date, there are also several tactical board tools and related ones for a wide range of team sports [7][17]–[25]. For instance, the Rugby 3D Sketcher [7] features 3DCG animation to display the movements of designated players. As described earlier, in this study, the integration function with this tool is implemented into our prototype tool [1][5]. Tactical Board Online [17] is an online tool supporting tactical boards for 35 team sports, including rugby, soccer, and basketball, providing overhead views from three perspectives: horizontal, half, and vertical. Tacbo [18] is a soccer-specific tool that can visualize Voronoi areas and Delaunay diagrams to help capture relationships among players geometrically. Other soccer-specific tools can also be obtained [19][20]. Moreover, reference [21] introduces a virtual reality-based tactical training system for basketball, which is equipped with a tablet-type tactical board tool to draw, select, or search for target player trajectories. To improve the effectiveness and experience of tactic training, this system visualizes player movements in virtual reality from input player trajectories. Additionally, a virtual magnetic tactical board tool for soccer is described in [22], which allows users to input player trajectories via virtual magnets on a virtual board to explore related situations from extensive data. Furthermore, video-based tactical analytical tools applicable to rugby matches, have also been identified [23]–[25], although these are not tactical board tools.

As this section details, many studies and tools have already existed for rugby and other team sports. However, in our investigation, we have not identified any rugby-specific tactical board tool enabling us to compute and visualize normative offensive sequences of running plays and hand-passing plays leading to tries, except for our prototype tool [1][5] that is the target of improvement in this study.

III. Overview of Computation Method [2]–[4]

In this section, we outline the computation method of a normative offensive sequence [2]–[4], which is incorporated in the prototype tool [1][5], as a preparation for discussing the improvements introduced in this study. Note that this section only describes its overview as related to this study; for more details, please refer to [2]–[4].

A. Formulation as Optimization Problem

This computation method [2]–[4] is based on an optimization problem with respect to offensive sequences composed of running plays and hand-passing plays. The objective function of this optimization problem consists of two metrics: the shortest time to score a try with the sequence and the expected number of times to be tackled by opponents during the sequence. In this optimization problem, a single offensive sequence is selected as an optimal solution from effective and feasible offensive sequences by minimizing the objective function, as follows:

$$\min_{p \in P^*} F(p), \ F(p) := T(p) + \lambda N(p). \tag{1}$$

Here, the symbol p indicates an offensive sequence, and the symbol P^* expresses the set of effective and feasible offensive sequences. The function $F(\cdot)$ describes the objective function, and the functions $T(\cdot)$ and $N(\cdot)$ compute the shortest time to score a try and the expected number of times to be tackled by opponents, respectively. The symbol $\lambda \in [0, \infty)$ signifies a parameter to adjust the trade-off between these two metrics in the objective function $F(\cdot)$. It is worth noting that there are no random factors in this optimization problem. Based on our preliminary experiments conducted with various values for the trade-off parameter λ and interviews with some rugby-experienced individuals in our previous studies [2]–[4], we have adopted $\lambda = 2$ as the default setting.

B. Implementation

In the actual implementation of this computation method [2]–[4], running plays of ball carriers and ball movements during hand-passing plays are simulated using a player motion model [6] and a ball motion model [2], respectively. The tackle probabilities of opponents during running plays, which are used to calculate the expected number of times to be tackled by opponents $N(\cdot)$, are evaluated based on players' reachable areas [6]. The players' reachable areas are also employed to evaluate catching possibilities of teammates and interfering possibilities of opponents to balls in hand-passes.

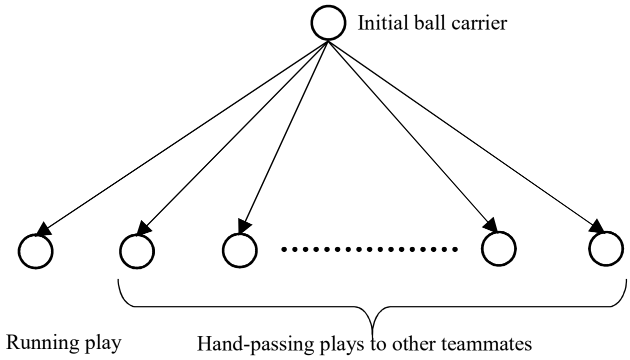


Fig. 1. Simple example of tree for offensive sequences [2].

While running plays and hand-passing plays are simulated as described above, the optimization with respect to offensive sequences (1) is executed by employing the branch and bound algorithm (for minimization problems) [26][27]. This algorithm is an exact algorithm that iteratively branches, dividing the original problem or a subproblem into smaller subproblems (child problems), and bounds, determining which subproblems do not need further solving.

Specifically, in the computing method [2]–[4], the branching of offensive sequences, including various running plays and hand-passing plays, is represented using a tree structure under several assumptions to apply the branch and bound algorithm [26][27]. The first assumption is that the ball carrier decides whether to continue running or to execute a hand-pass to other teammates for a fixed time interval Δ[s] (Δ = 1 in our default setting). The second assumption is that the ball carrier runs with maximum force within the time interval Δ[s] when they decide to continue running. That direction is also assumed to be determined by minimizing the objective function $F(\cdot)$ in (1) if the ball carrier continues running with constant directional maximum force until they score a try by themselves. The third assumption is that the ball-catching teammate (the next ball carrier) catches the ball at the location that minimizes the objective function $F(\cdot)$ if this player runs with constant directional maximum force until scoring a try after the catch. That direction is also assumed to be decided in the same way as in the second assumption. The last assumption is that the ball-catching teammate does not execute a hand-pass immediately after the catch; that is, the catcher runs for at least the time interval Δ[s] after the catch. That running force is also assumed to be decided in the same way as in the second assumption.

Fig. 1 illustrates a simple example of a tree representing offensive sequences considered in the computation method [2]–[4]. The figure depicts seven branches: one where the ball carrier continues running and six where they hand-pass to each of their remaining six teammates. Note that, in the branch and bound algorithm [26][27], each node of the tree corresponds to a (sub)problem for optimizing the rest of the sequence (up to a try), where the plays leading up to the node are fixed.

C. Update for Expected Number of Times to Be Tackled

This subsection provides an explanation as we have updated the calculation scheme for the expected number of times to be tackled by opponents $N(\cdot)$ appearing in (1) from the previous scheme used in [2]–[4]. In the computation method [2]–[4], the expected number of times to be tackled by opponents $N(\cdot)$ is computed by summing the tackle probabilities for all opponents, which are evaluated based on players' reachable areas [6]. Moreover, in the previous scheme [2]–[4], when multiple running plays occur within a single sequence, the expected number $N(\cdot)$ is computed by summing up the simple sum of tackle probabilities of each opponent. However, a single opponent's sum can exceed 1. Obviously, this is unrealistic because it is typically difficult for a single opponent to make multiple tackles within a single sequence. Therefore, in the previous scheme [2]–[4], when the sum of an opponent's tackle probabilities exceeds 1, the sum is truncated to 1.

However, assuming opponents move rationally, it is more natural to hypothesize that they will direct their tackling efforts towards the running play where their tackle probability is highest. That is, for a single opponent, it is more suitable to use the maximum value of the tackle probabilities than their sum. Therefore, the current scheme computes, for each opponent, the maximum value of the tackle probabilities across all running plays. Then, the expected number $N(\cdot)$ is computed by summing these maximum probabilities across all opponents.

IV. Improving Prototype Tool

In this section, we present two improvements to the prototype of the intelligent tactical board tool [1][5], which is equipped with the computation method of a normative offensive sequence [2]–[4] mentioned in the previous section. Specifically, first, we outline the prototype tool [1][5]. Then, we detail the first improvement: computing multiple normative offensive sequences. Lastly, we explain the second improvement: the integration function with the 3D visualization tool Rugby 3D Sketcher [7].

A. Overview of Prototype Intelligent Tactical Board Tool

This prototype tool [1][5] consists of three windows designed to facilitate the execution of the computation method [2]–[4], allowing easy input of players' position and velocity information: (a) Operation window equipped with buttons for operations such as loading/saving players' position and velocity information, and executing the computation method [2]–[4] with specified player position and velocity information. (b) Tactical board window for inputting players' position and velocity information, enabling specification and modification of players' position and velocity information through click and drag operations. (c) Display window for displaying an animated offensive sequence computed by the computation method [2]–[4].

B. Improvement for Computing Multiple Sequences

As previously mentioned, the computation method described in [2]–[4], which has been implemented into the prototype tool [1][5], employs the branch and bound algorithm (for minimization) [26][27]. This algorithm bounds subproblems when the lower bounds of their optimal objective function values exceed the current upper bound of the optimal objective function value of the original problem. Therefore, this algorithm, as it is, cannot guarantee the computation of the top multiple sequences, except for the optimal one, because it uses the upper bound of the optimal value of the original problem for its bounding operations. In other words, the top multiple sequences, except for the optimal one, may be pruned by the bounding operations. Note that there exist several studies related to the branch and bound algorithm for computing top multiple solutions to the knapsack problem (e.g., [28]). However, based on the authors' investigation, no methods from such studies can be directly applied to the optimization problem (1) addressed in this study due to the inherent differences in problem characteristics.

To overcome this, we simply need to use the upper bound of the top K-th value of the original problem, rather than that of its optimal value, in the bounding operations ($K \geq 2$). In that case, it can guarantee the computation of the top K sequences; namely, the top K sequences are never pruned in the bounding operations. Therefore, the current implementation in the prototype tool [1][5] maintains the objective function values of explored offensive sequences (i.e., simulated up to a try) in a descending-order priority queue of capacity K. Then, the bounding operations use the K-th highest value stored in this priority queue up to that time. With this implementation, the current prototype tool can output K offensive sequences by the end of the process.

C. Integration Function with 3D Visualization Tool

In the prototype tool [1][5], the normative offensive sequences displayed in the display window are difficult for users to intuitively understand. Two main reasons account for this. The first reason is that, although they are animated, the computed sequences are depicted using only dots and lines from a perspective view. The second reason is that the information of all players except for the ball carriers (and even the ball carriers before receiving the ball) is depicted only by their reachable areas [6] and the center points of those areas, without illustrating their specific movements. To address these issues, in this study, we implement an integration function with the 3D rugby tactical visualization tool, Rugby 3D Sketcher [7], to visualize the computed sequences using 3DCG animation from many viewpoints, including those from players and coaches, as well as from arbitrary points on the field.

Specifically, we first build a subfunction to export computed offensive sequences in XML format, compatible with Rugby 3D Sketcher [7]. This XML file includes position data of players and the ball, enabling animations to be rendered accordingly in Rugby 3D Sketcher [7]. Then, we implement another subfunction to inverse-calculate movements of several players using the player motion model [6]. In this subfunction, the target players include the ball carriers before receiving the ball and the opponents with high tackle probabilities. Its inverse-calculations are based on the information from the target sequence, such as their ball catching times and locations, and their times and locations where their tackle probabilities exceed a threshold. These inverse-calculated movements can also be visualized in Rugby 3D Sketcher [7] through the first subfunction.

V. Functional Validation Test Using Real Formation

In this section, we describe the functional validation test conducted for the functions newly incorporated into the prototype tool [1][5] as described in the previous section, using a real formation example extracted from a video of an actual rugby sevens match.

A. Test Conditions

This test uses, as previously mentioned, an example extracted from a video of an actual rugby sevens match. The video is included in the video material [29], and the match is the Rio de Janeiro Olympic Men's Sevens Rugby preliminary round C match between New Zealand and Japan. Fig. 2 depicts the positions and velocities of players in the target

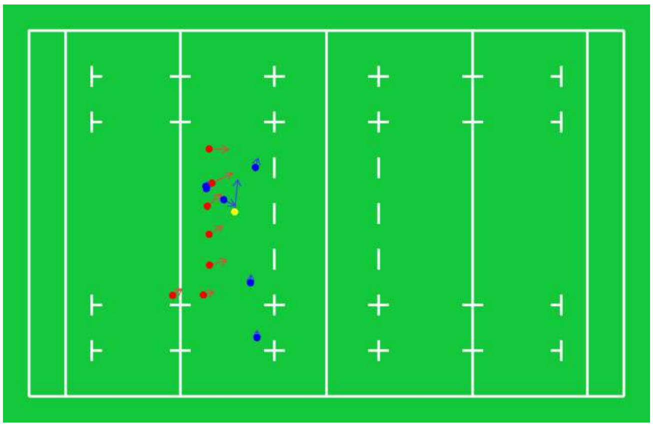


Fig. 2. Players position and velocitie information in target formation example.

TABLE I. PRIMARY PARAMETER SETTINGS

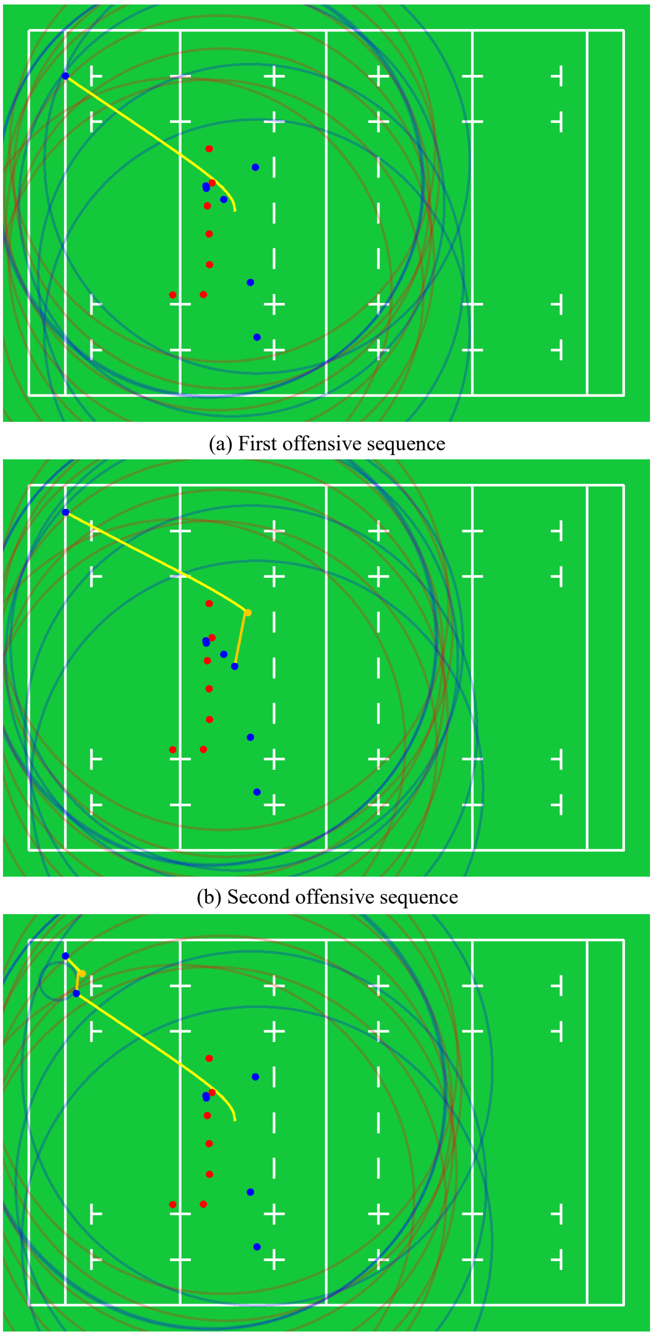
Parameters		Values
Adjustment parameter for trade-off in objective function: λ		2.0
Running acceleration ability	Ball carrier	1.56 s^{-1}
	Non-ball carrier	1.46 s^{-1}
Maximum running speed	Ball carrier	8.48 m/s
	Non-ball carrier	8.63 m/s
Decision-making time interval: Δ		1.0 s
Hand-passing speed		18.0 m/s
Hand-passing effective range		20.0 m
Simulation time step		0.05 s

example displayed on the prototype tool [1][5]. In this figure, yellow marker denotes the position of the ball carrier, while blue and red markers indicate the positions of teammates and opponents, respectively. Vectors from the markers represent the velocities of the players corresponding to the markers. The lengths of the vectors equate to the distances the corresponding players can advance in one second at their respective velocities. Note that, in the actual situation, the ball carrier attempted to break through between the second and third opponents from the top after this moment; however, he was surrounded by two opponents, tackled, and fell as a result.

The parameter settings in this test align with those detailed in [2]–[4], and TABLE I shows the setting values of the primary parameters. Here, the values related to running abilities have been estimated from sprint times sourced from [30], accounting for differences between ball carrier and others. Meanwhile, the values on hand-passing abilities have been determined by referring to data presented in [31][32].

B. Results on Computing Multiple Sequences

This subsection presents the test results for the newly incorporated function to compute multiple offensive sequences against the aforementioned example. Here, we set the number of sequences K to 3. Fig. 3 presents the top three computed sequences, at the moments of scoring tries, displayed on the prototype tool [1][5]. In this figure, the blue markers indicate the positions where the last ball carriers scored tries, the positions where previous ball carriers made hand-passes, and the initial positions of teammates. The light orange markers indicate the catching positions of the hand-passes. The red markers denote the initial positions of opponents. The trajectories of the running of the ball carriers and of the ball during hand-passes are drawn by the yellow and the light orange lines, respectively. The reachable areas [6] of teammates and opponents, at the moments of scoring tries, are shown by blue and red circles, respectively.



(a) First offensive sequence

(b) Second offensive sequence

(c) Third offensive sequence

Fig. 3. Top three sequences displayed at moments of scoring tries by prototype tool.

As shown in Fig. 3 (a), the first offensive sequence computed for this example is a running play where the initial ball carrier runs to the upper-left area, going just above the second opponent from the top. In the second computed sequence described in (b), the initial ball carrier makes a hand-pass to the teammate positioned above, who then runs to the upper-left area to score a try. From (c), we can observe that the third sequence is the same as the first sequence up to a certain point. At this point, the first ball carrier, just in front of the opponent's in-goal area and about to be caught in the reachable area of an opponent, executes a pass to a teammate positioned slightly above him. Therefore, from this figure, it

(a) First offensive sequence

(b) Second offensive sequence

(c) Third offensive sequence

Fig. 4. Selected moments of top three sequences visualized from overhead view behind scoring ball carrier by Rugby 3D Sketcher [7].

is confirmed that the top three computed sequences are fairly different from each other. Moreover, all of the top three computed sequences seem to more effectively avoid opponents' tackles compared to the actual situation where the first ball carrier boldly but riskily attempted to break through between the second and third opponents from the top. These facts indicate that such a new function can adequately provide a broader range of options for coaches and players in practical usage situations.

C. Results on Visualizing with 3D Visualization Tool

This subsection describes the test results for the integration function with the 3D rugby tactical visualization tool, Rugby 3D Sketcher [7], to visualize the computed sequences using 3DCG animation.

Fig. 4 illustrates a selected moment for each computed sequence from an overhead view behind the scoring ball carrier, visualized with Rugby 3D Sketcher [7] via the integration function. In this figure, the players in blue uniforms represent the positions of the teammates, including the positions where the previous ball carriers executed hand-passes and the current positions of the ball carriers. In contrast, the players in red uniforms indicate the positions of the opponents, including the positions where the opponents with high tackle probabilities attempt to tackle the ball carriers. Specifically, these positions were determined as the positions where the tackle probabilities exceed a threshold of 0.5. Additionally, the current ball carriers are encircled in red. The light blue dashed lines denote the trajectories of the ball carriers' running, including the trajectories before receiving the ball. The orange dashed lines represent the running trajectories of the opponents with high tackle probabilities attempting to tackle the ball carriers.

From this figure, we can easily observe that the computed sequences are more effectively visualized by 3D Sketcher [7] via the integration function implemented in this study. In particular, this figure confirms that 3D Sketcher [7] via the integration function effectively demonstrates the running trajectories of the ball carriers before receiving the ball and those of the opponents with high tackle probabilities attempting to tackle the ball carriers, although these trajectories are not displayed in the tactical board tool [1][5]. Therefore, it can be said that the integration of 3D Sketcher [7] with the newly implemented function is confirmed to transform the computed sequences into more intuitively understandable representations for players and coaches.

On the other hand, we can find potential for further enhancement of the visualization from this figure. Concretely, in the current implementation, the movements of opponents with high tackle probabilities are only calculated. However, some of the other opponents should also move in the visualization. For example, in the first and second computed sequences, the last ball carriers are about to be caught in the reachable areas of opponents at the moments of scoring tries, as shown in Fig. 3. Moreover, in the third sequence, the first ball carrier, about to be caught in the reachable area of an opponent, executes a pass, as mentioned in the previous subsection. In such cases, it is considered reasonable to visualize the movements of these opponents. Nevertheless, in the current implementation, the movements of these opponents are not visualized as presented in Fig. 4, because their tackle probabilities are lower than the threshold or zero. We are currently working on this issue and will present its result in the near future. Subsequently, further evaluations with rugby players and experts in rugby tactics are planned to be conducted using multiple formation examples.

Furthermore, we measure the numbers of processed nodes and processing time for computing the single offensive sequence using the same program as in [4] and for computing the multiple offensive sequences using the program in this study with $K = 3$. For this measurement, we use a parallel computer with 24 cores and 48 threads (OS: CentOS Linux release 7.6.1810 (Core), CPU: AMD EPYC 7402 (24Core 2.8GHz 128MB)×2, Memory: 16GB DDR4-3200 REG ECC (total 256GB)). As a result, in the former case, the numbers of processed nodes is 98 for bounded nodes and 1 for try nodes (leaf nodes). In contrast, for the latter case, these numbers are 344 and 10, respectively. Additionally, the average processing time over 10 trials is 2.16 seconds for the former and 7.56 seconds for the latter. Thus, increasing the value of K naturally increases both the numbers of processed nodes and processing time. However, it is confirmed that, at least for K

= 3 in this formation example, the processing time remains practically realistic. Yet, for accommodating larger values of K, we also consider exploring more efficient computational methods as future work.

VI. Conclusions

In this study, to provide a broader range of options to coaches and players, we enhanced our prototype of an intelligent tactical board tool so that it can compute multiple normative offensive sequences serving as references. Moreover, to make the visualization of the computed offensive sequences more intuitively understandable for players and coaches, we implemented an integration function with the commercially available 3D visualization tool for rugby plays [6] into this prototype tool. To confirm the functionality of the improved tool, we conducted a validation test using a real formation example from a video of an actual rugby sevens match. As a result, we confirmed a part of its effectiveness. The future work includes further improvements and evaluations described in the previous section.

Acknowledgment

We would like to express our sincere gratitude to L. Tournier of Tactic3D for his valuable advice. Additionally, we are thankful to Y. Tokutake at our laboratory and S. Ryuzaki, a former member of our laboratory, for their supports.

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