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Design of a handball tactics observatory based on dynamic sub-graphs

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Abstract. We propose the design of an observatory dedicated to the tactical analysis of handball, involving the use of *dynamic graphs* to represent and study patterns of play. This innovative methodology was used to capture the complex interactions between players, their movements on the court and passing sequences. By using techniques for extracting frequent subsequences from a dynamic graph constructed from a *gnomonic* transformation³ of the court, it was possible to identify the most recurrent and therefore significant patterns of play. The extracted sequences were valued by various measures of interest: emergence rate and *expected goal*. These measures of interest introduced a hierarchy between the sequences, enabling them to be navigated. Within the observatory, the tactics discovered were illustrated by an intuitive graphical representation, giving coaches and analysts a better understanding of the trends, strengths and weaknesses of the tactics employed.

Keywords: sports analytics · dynamic graphs · handball observatory

1 Introduction

Handball is well studied in the literature on aspects of coordination, agility, strength and power, endurance, constitution, social factors, cognition (see [57] for an extensive review). However, tactical and strategic approaches are minor. With the exception of [11, 33, 48, 55], the collective aspects of handball are very little studied. However, it is a sport where the collective aspect dominates. In addition, it produces a large number of stereotypical positioned sequences and tactics are well documented: looking for recurring combinations should be fruitful.

The identification of these recurrences would allow an automatic indexing of sequences in the match, the automatic generation of summaries (in handball, there are a lot of goals, which ones are particularly interesting?) – see [9, 52, 58] for soccer – and in fine the detection of the characteristic routines or formation [28] of a team, in order to obtain a competitive advantage.

³ azimuthal map projection that transforms circles into straight lines.

Here we transposed the notion of observatory to the field of handball. This notion comes from linguistics, where the corpus is an *observatory* of a theory a priori, it is also a dynamic observation that can be used to describe and then develop a posteriori models [25,36]. The various activities of the observatory can be classified into three segments of intervention: an activity of production and dissemination of knowledge; an activity of a strategic nature through the production of analysis notes, sheets or elements of language concerning the situation of the subject; and an activity of an operational nature by organizing actions and putting in place tools [35,43]. Our corpus consisted of handball data from the 2015 World Championship in Qatar. Our ambition was to analyze tactics in handball by acting on the three segments of intervention mentioned above: disseminating knowledge on tactics, producing analysis notes and implementing analysis tools.

To analyze the tactics used, it was important to consider the sequence of events in a handball match as recorded in the data available to us. In practice, we had the trajectories of the players and a succession of events (pass, shot, foul, etc.). The notion of *dynamic graphs* was used to capture the dynamic evolution of the game. A graph is a mathematical structure considering a set of *nodes* which are the entities of the game and a set of *edges* indicating the relationships between the nodes. A dynamic graph is one that evolves over time.

A tactical element is a short succession of events. This element is interesting if it tends to recur frequently, which gives it the nature of a *pattern*. This interest arises from the reproduction of the situation and the characterization it gives to the team executing this tactic. The tactics we propose to analyze were therefore the result of extracting frequent subsequences from the dynamic graph associated with the game. This method produced knowledge that could be used to activate the observatory's first intervention segment. The second segment, dedicated to the production of analysis notes, would be supported by the creation of an interface for displaying the tactics detected.

This focus on dynamic graphs is original. Even in soccer, where there are many studies on the training of players, in terms of spatial organization, the state of the art emphasizes that no method performs a real-time analysis of the dynamics of tactics. Most of the time, aggregations on possession time are analyzed. For rugby, a specific study dynamically analyzes static graphs by looking at the relationship between connectivity, assortativity, strongly connected components and clustering on the player/pass/tackle graph and looks for a correlation with the amount of progression made [6].

The automatic analysis of trajectories in search for tactics complements the expertise of the coach. The techniques implemented were agnostic in that they made no presuppositions about the activity and proposed an objective analysis of it: the trajectories were transformed into dynamic graphs within which an exploratory approach was applied in search of regularities. These regularities were provided with measures of interest to encourage interaction with the expert using the observatory. We believe that this methodology and the resulting tools enriched the expert's analysis and discovery capabilities.

The article is organized as follows: Section 2 sets out the state of the art, Section 3 presents the data studied and then Section 4 presents the construction of the dynamic graph based on a transformation of the court where the trajectories occur. Section 5 analyzes the results obtained from the court transformation and the creation of an interface for enhancing the extracted tactics.

2 State of the art

The search for collective regularities is a classic task in the analysis of sports trajectories, as attested by [17], which provides a very comprehensive synthesis of research into temporal analysis for team sports. This search for regularities requires a *vector quantization* from the continuous spatial domain to a *symbolic* domain. The problem of identifying trajectory patterns then becomes a problem of searching sequences of symbols, on which qualitative spatial reasoning is possible [5]. For example, spatial relations are encoded in a logic formalism that allows the prediction of the next pass in football using inductive logic programming [56].

Discretization of the spatial domain is a two-stage process: characterization / detection of an object of interest, which makes it possible to aggregate continuous position data, then grouping of objects of interest / reduction of the dimension in order to limit their number.

For the second phase of grouping objects of interest, we can distinguish between the use of k-means or EM clustering in [1, 2, 10, 11], dimension reduction (PCA) in [44] or optimized tensor reduction [32], the use of self-organizing cards [30] or neural gas [34] in [15, 16, 21, 27, 40, 48, 55], and finally the calculation of neighbors by dynamic time deformation [18].

An optional third stage in this process of transforming the space of trajectories into a series of movements concerns the classification of the movement (a series of displacements), often by comparison with the various representatives of the clusters [16].

2.1 Handball

We will not go into the details of the many studies on the individual aspects during the practice of handball (see for example [21, 22, 24, 37, 42, 45]). However, contributions on collective aspects are few and far between: in [55], eight cameras detect the position of the defender in front of the shooter in order to create self-organizing Kohonen maps [30], a clustering method which can therefore be used to characterize defensive behavior. The same technique is used in [48] but for attack: sequences of five passes before the shot are grouped together, highlighting the eight most-played sequences out of a total of 612 over 6 matches. Finally, [33] analyses a sequence of temporal patterns (T-patterns [26]) to characterize defensive behavior.

2.2 Searching for temporal regularities

The first step in the search for regularity in collective motion patterns is to characterize the objects of interest. This task is well identified, see for example [8] which provides an extremely precise and detailed taxonomy of collective motion patterns. Once this discretization of the spatial domain has been carried out, it is possible to undertake qualitative spatial reasoning [5]: the spatial relationships are encoded in a logic formalism which allows the next pass to be predicted using inductive logic programming [56].

Spatial collective patterns (*generic aggregation patterns* [31]), although classic in the trajectory analysis community (flock, dominance, convergence, confrontation), are little used in sport. Instead, one can find the *temporal patterns* (T-patterns [26]), which are hierarchical sequences of events, hierarchical in the sense of nesting and relationships between components, for example in [33]. Techniques derived from Kohonen’s concept maps are also favored for their ability to perform spatial clustering [15, 16, 21, 27, 40, 48, 55].

Finally, there is the use of constellations [11], which describe the relative position of objects in relation to each other, depending on their distance. A constellation is thus invariant to rotation and dilation. This approach is applied to football in [10].

2.3 Dynamic graph

A graph $G = (V, E)$ associates a set of nodes V with a set of edges E , which are pairs of nodes. A graph is used to model the relationships between entities in a system. This graph is said to be *static*, as opposed to a *dynamic* graph whose edges and nodes change over time.

A dynamic graph $(G_t)_{t=1..T}$ is therefore defined as a sequence of static graphs (or *snapshot*) G_1, G_2, \dots, G_T where each G_t represents the state of the graph at a given time t . Formally, $(G_t)_{t=1..T} = (V_t, E_t)_{t=1..T}$, where V_t is the set of nodes in G_t at time t and E_t is the set of edges at time t [23].

The time t indexing the dynamic graph depends on the representation chosen for the data. For example, for our data from the World Championship in Qatar, the trajectories are sampled at 10 Hz. The time t here could be an integer number of tenth of a second. We could also consider only the sequence of graphs corresponding to each pass, ball reception, shot or foul event. In this case, t would be an integer index of the total number of events.

The same dynamic graph can be represented in a number of equivalent ways [23]: temporal graph, dynamic or temporal network, evolutionary graph, sequence graph, chronological series of graphs, and so on.

Classical approaches use a sequential representation where each instant is modelled by an adjacency matrix $(A_t)_{t=1..T}$, describing the presence or absence of edges between nodes at time t [51]. Other temporal models capture the evolution of the graph by assigning time intervals to the edges, making it possible to follow the evolution of the connections between the nodes. In this way, each

edge is characterised by a triplet $(v_i, v_j, [t_{\text{start}}, t_{\text{end}}])$, indicating that the edge exists between the nodes v_i and v_j during the time interval $[t_{\text{start}}, t_{\text{end}}]$ [12].

Evolutionary graphs combine the structure of a static graph with a sequence of states. They are suitable for modelling systems that evolve continuously, such as social networks. Evolutionary graphs $(G_t)_{t=1..T}$ incorporate the static structure of a graph G and an evolution function ϕ such that $G_t = \phi(G, t)$. This function can describe changes in the graph topology over time [46].

3 Data

There are two types of dataset for team sport: spatio-temporal data and event data. *Spatio-temporal* data are the trajectories of players or the ball; they provide location, direction and speed information for each of the entities [17]. *Event* data provides logs of player-related events (pass, shot, reception, goalkeeper save, etc.) or technical events (red card, start of time, stop of time, foul, etc.) for a match. These data are the result of manual annotations. Each of these events can be associated with a distance, duration or direction and has a time stamp.

These two ways of looking at data require different technologies and technical or financial resources. For example, sensors Indoor Position System (IPS) [50] are inexpensive but not very accurate, while video [41, 47, 49] is accurate but requires costly treatment.

The data analyzed here comes from 88 matches of the 2015 Handball World Championship held in Qatar. These data were obtained by video analysis and manual annotation of the events. This dataset has been little studied, and only on individual aspects [4, 19, 20].

This data combines spatio-temporal and event-based information: the trajectory of each player at 10 Hz and details of match events such as passes, receptions, shots and goals. For each match, a statistical summary table is available for each player. This table provides individual information, such as walking distance, running distance, shooting distance at 7m and 9m and the player's role for each match.

4 Handball tactics based on dynamic sub-graphs

In this section, we present our main contribution to the construction of a dynamic graph of the handball game based on the player trajectories available to us. We begin by justifying the use of the Delaunay graph, whose dynamic is encoded by a difference dynamic graph. We then introduce a gnomonic transformation to take better account of the particular topology of the handball court. We conclude by explaining how we extracted tactics from frequent dynamic sub-graphs and indicate how the relevance of these tactics is evaluated.

4.1 Transformation of trajectories into graphs

To transform the available data into dynamic graphs, we first needed to choose the entities represented by the nodes and the relationships between these entities,

which would be represented by the edges. The handball entities are naturally the players and the ball.

Each player could be considered individually or according to its position. In the first case, a tactic would be personalized by a specific player and a same different tactics could be instanced by different players. In the second case, the player’s position was taken into account, rather than the individual, as a collective movement involves roles rather than specific people. The interface we proposed in the next section allows to choose between these different configurations. The default setting proposed individualizing the members of the French team and grouping their opponents by position.

As for the ball, it could be considered as a particular entity and give rise to a node in the graph. We could also consider that the player entities had a particular attribute which indicated possession of the ball. We have chosen to consider the ball as a particular entity.

To construct the dynamic graphs in which we are going to explore the recurring patterns, we needed to transform the players’ positions into graphs. If the choice of entities that defined the nodes was clear (the players and the ball), how should the edges that symbolize the relationships between the entities constructed? There were many possible choices for this; define the neighborhood of each player, which groups together the other closest players; consider the positions of each player and construct the graph according to the relative positions of each player in attack/defense.

However, it would be preferable for the transformation into a graph to be non-parametric and *agnostic* (i.e. not require any prior knowledge of handball, for example). We therefore recommended using the *Voronoi diagram*, which shows the zones that a player can reach before all the others if they all have the same speed. It is a tool used in many scientific contributions linked to sport, for example football [29]. Voronoi zones are bounded by the bisectors of the segments joining two players⁴.

The Delaunay triangulation [7] of a set of points is presented as the dual graph of the Voronoi diagram. Each cell of the Voronoi diagram is represented by a vertex in the Delaunay triangulation, and these vertices are connected by edges when the corresponding cells are adjacent. The boundaries of the Voronoi zones are determined by the bisectors of the segments connecting two nodes. To transform the raw data into a graph structure, we calculated the zones of influence at each point in time, then used Delaunay triangulation to encode a match in the form of a dynamic graph.

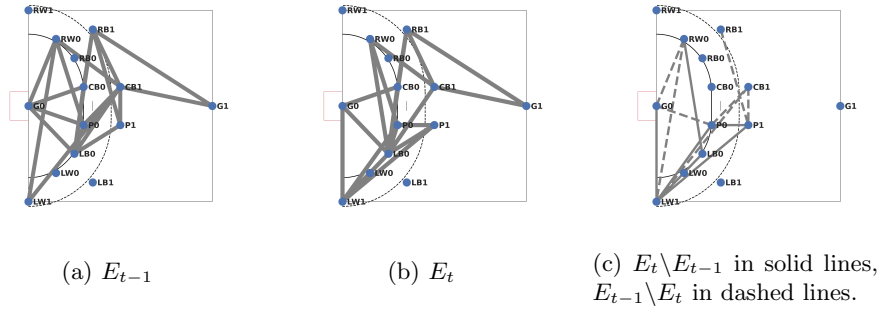
⁴ this definition assumes that each player evolves at the same speed. The notion of dominant regions [54] or areas of influence [53], taking into account various factors such as speed, orientation vector, etc., are closer to the reality. There are also contributions based on probabilistic models of movement and control zones [3, 14].

4.2 Event differential encoding

To encode the dynamic graph, we chose the event difference. At each instant t , we examined the changes in the Delaunay triangulation relative to $t - 1$: we noted which edge appeared or disappeared. Persistent edges were ignored.

In the end, rather than $(G_t)_{t=1..T}$, we therefore considered the *dynamic difference graph* [39] $(\Delta G_t)_{t=2..T} = (V_t, E_{t-1} \setminus E_t, E_t \setminus E_{t-1})_{t=2..T}$ where $E_{t-1} \setminus E_t$ is the set of vanishing edges and $E_t \setminus E_{t-1}$ those appearing when $t - 1$ changes to t . Figure 1 provides an example of two snapshots G_{t-1} and G_t with their edge sets E_{t-1} (Figure 1a) and E_t (Figure 1b); their differences $E_t \setminus E_{t-1}$ and $E_{t-1} \setminus E_t$ are at Figure 1c.

Fig. 1: Difference graph.



Event difference encoding offers a fine granularity for capturing changes in the structure of the dynamic graph. In a sporting context, where interactions between players evolve rapidly, this approach provides a precise representation of the moments when new connections are formed or dissipated. This makes it easier to analyze key moments in the match, such as the formation of new tactics or the break-up of the opposing team. In addition, the event difference makes it possible to eliminate stationary edges, which would generate a large number of uninteresting frequent patterns.

Finally, as our data concerned several matches, each with two halves, extra time, stoppages in play, etc., we had to manage a dynamic graph *database*. More precisely, we considered having a dynamic graph for each series of five passes preceding a shot. This choice was justified by the desire to determine the tactics applied when approaching the shot and corresponded to the rhythm of collective movement in handball.

4.3 Conversion of the handball court

A handball court has an atypical topography: the area is rounded and the defenders position themselves around it to form a wall in front of the goal. This

area is off-limits, unlike in football or basketball. Taking the straight line between two points, which in theory is the shortest route, is not always possible: you have to go around the forbidden zone. This prohibition changes the spatial relationships between players.

However, the aim of a Voronoi diagram is to account for the influence of the players on the court, and the conventional geometry used for this purpose does not take account of the particular topography of the handball court. In order to take better account of the spatial relationships between the players, we proposed to *transform* the initial court (Figure 2a) by *curving* the area using a *gnomonic* transformation, so as to create a geometry in which a straight line is the shortest path between two points (see Figure 2b). The Voronoi diagram was then calculated for this transformation. Next, the *inverse transformation* was applied, to obtain the Voronoi diagram for the initial court with *curvature* of the zone (see Figure 2c).

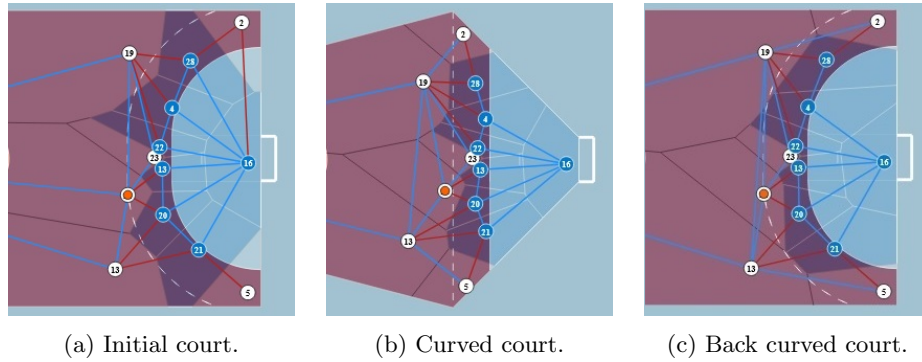


Fig. 2: Voronoi diagram and Delaunay triangulation for successive transformations of the court.

Let M have coordinates (x, y) . Let O be the center of the quarter circle of the zone. Let $r = OM$ and θ be the angle (Ox, OM) (see Figure 3).

The transformation of the court, which turns the quarter-circle zone into a segment, had the equation:

$$\begin{cases} x' = r \\ y' = r \cdot \frac{\theta}{\frac{\pi}{2}} \end{cases} \quad (1)$$

The level curves shown in Figure 4 corresponded to the constant abscissa lines on the curved court.

4.4 Extraction of recurrent subsequences

To extract the frequent dynamic sub-graphs that represented the tactics, the dynamic graphs were converted into sequences of sets of edges. The frequent *closed*

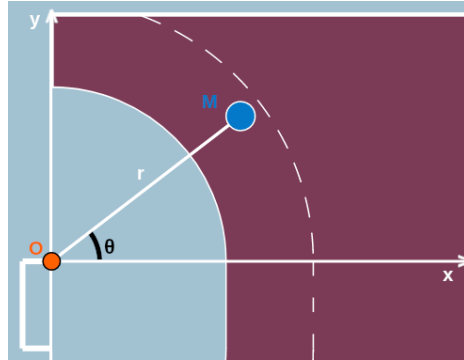


Fig. 3: Representation of a quarter of a plot.

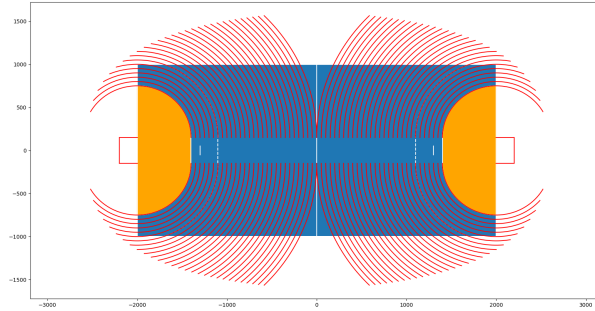


Fig. 4: Level curves (in red) on the court.

subsequences were then extracted from these sequences [13]. A subsequence is *closed* if the addition of elements to this sequence reduces its frequency and therefore its representativeness. For example, if the algorithm determines that the sequences $\langle B, C \rangle$ (event C follows event B) and $\langle B, C, D \rangle$ has the same frequency, then $\langle B, C \rangle$ is not closed and will be ignored. And if any sequence constructed from $\langle B, C, D \rangle$, for example $\langle A, B, C, D \rangle$ or $\langle B, C, D, E \rangle$, has a lower frequency than $\langle B, C, D \rangle$, this means that $\langle B, C, D \rangle$ is closed. This technique avoids a lot of redundancy and focuses attention on the essential frequent sequences.

In addition, the algorithm was provided with temporal constraints, for example constraints on the temporal distance between the elements of the subsequences obtained. Here, we required that the elements pointed to were consecutive in the data, in order to obtain frequent sequences that represented a sequence of *consecutive* events. Otherwise, the algorithm could display sequences of events belonging to distant phases of the game, for example an event during the first quarter, followed by an event during the second, then the third, and so on. It was essential that the information obtained was representative of a se-

quence of consecutive events. Using temporal constraints, it was guaranteed that the subsequences extracted from our database of sequences of five passes before a shot showed a succession of events that occurred during a single sequence of five passes before a shot, and not straddling several sequences.

4.5 Measures of tactical interest

The extraction algorithm provided a large number of tactics. In order to facilitate access to relevant tactics, these had to be sorted according to measures of interest. Here we proposed three different measures: support, expected goal (xG) and emergence rate. *Support* counted the number of game sequences in which a tactic occurs. *Expected goal* is a statistical measure indicating the probability of scoring at the shot position at the end of a sequence. This measure was obtained using a model trained on data from Qatar 2015 and fed by the position of the shooter [38]. Finally, the *emergence rate* measured the ratio between the number of successful (giving a goal) and unsuccessful occurrences of the tactic.

Note that the emergence rate is a *forward-looking* or *anticipatory* measure, as it refers to the evolution of the situation it measures. In contrast, the expected goal is a *retrospective* measure because it is provided by a model calculated on the basis of aggregated data. The expected goal is therefore not directly influenced by developments in the situation being characterized.

While the emergence rate provided information about the profitability of a tactic, the advantage of the expected goal measure was that it did not make any assumptions about the quality of the shooter or the goalkeeper. Expected goal provided information on the quality of the situation in which the shooter was placed to take the shot, independently of the quality of the shot that follows. This measure was therefore appropriate for the objectives we had set ourselves, which were to show the effective reasons for putting the shooter in a very favorable shooting condition.

5 Results

5.1 Relevance of the court transformation

In order to determine the impact of the court transformation (decurvature then recurvature), we counted the edge differentials between the initial graph and the transformed graph. To do this, we aggregated each game situation according to the player’s position: Goalkeeper (G), Left Wing (LW), Right Wing (RW), Center Back (CB), Left Back (LB), Right Back (RB), Pivot (P). The defending team was marked 0 and the attacking team was marked 1. For example, CB0 indicated the center back in a defensive position.

Table 1 and 2 show the counting results, while Figure 5a and 5b give a quantitative interpretation. The tables count the size of the reference set (initial or transformed graph), the size of the intersection (with the transformed or the initial graph) and then the difference. Comparative analysis of the dynamic

edges	initial	intersection	initial \ transformed	ratio (%)
(G0, RW1)	1120	192	928	82,8
(RW0, G1)	1106	216	890	80,5
(RW1, G0)	1114	357	757	68,0
(G1, RW1)	3321	1930	1391	41,9
(RW0, G0)	3993	2999	994	24,9
(RW0, RB1)	3707	2869	838	22,6
(CB1, RB0)	5247	4370	877	16,7
(G1, CB1)	6045	5258	787	13,0
(RB0, G0)	6850	5975	875	12,8
(RW1, CB1)	2279	2213	66	2,9
(RB1, RW1)	2510	2444	66	2,6
(RW0, CB0)	3230	3153	77	2,4
(RW0, CB0)	3146	3080	66	2,1
(RW1, CB1)	3305	3237	68	2,1
(RB0, RW0)	2064	2034	30	1,4

Table 1: Edges lost through court deformation.

edges	transformed	intersection	transformed \ initial	ratio (%)
(RB1, RW1)	3968	2444	1524	38,4
(RB0, RW0)	3081	2034	1047	34,0
(LW1, LB1)	4659	3237	1422	30,5
(LW0, CB0)	4285	3080	1205	28,1
(LW1, CB1)	3025	2213	812	26,8
(LW0, LB0)	4113	3153	960	23,3
(LW0, RB1)	3255	2869	386	11,9
(G1, RW1)	2114	1930	184	8,7
(LW0, G0)	3256	2999	257	7,9
(LB1, RB0)	4679	4370	309	6,6
(RB0, G0)	6208	5975	233	3,8
(LW0, G1)	222	216	6	2,7
(G1, CB1)	5394	5258	136	2,5
(LW1, G0)	363	357	6	1,7
(G0, RW1)	194	192	2	1,0

Table 2: Edges created by court deformation.

length	number	support	ρ	xG
2	4,836	26.88	1.56	0.58
3	1,420	26.82	1.68	0.58
4	392	26.22	1.30	0.56
5	172	25.23	0.97	0.58
all	6,820	26.88	1.55	0.58

Table 3: Tactics and relevancy measure by size.

visualization interface, both to select a tactic for scrutiny and to contextualize it within the match. This interface enabled activation of the observatory’s second intervention segment by generating analysis notes.

The knowledge produced by the tactics extractor was *objective*, as no assumptions were made about the activity in question. Our method did not use any model for handball interaction: trajectory segmentation was performed using the Delaunay graph, and tactics were obtained by extracting regularities. To involve the expert in the analysis of our results and bridge the semantic gap between our disciplines, it was important to favor a holistic approach by situating the obtained results within the framework of handball activity: edge sequences should be visualized on a player position diagram, integrated into the course of a match.

The interface should offer the expert considerable freedom to choose among the many discovered tactics. While the currently analyzed tactic naturally occupies a central position within the interface (zone 1), it is possible to select priority orders for the whole set (zone 2): attack or defense, associated interest measure (xG, emergence, support), pattern length, place attack or counter-attack, triggering position within the data sequences. The currently visualized tactic then has statistical measures (zone 3) relative to the entire data set, associated with the order selector: xG, emergence, support, triggering position. More sports-oriented semantic measures (zone 4) allow the expert to diversify potential explanations for the pattern’s interest and to place it within the sequence from which it originates: xG, triggering, opponent pressure (number of links between the ball and opponents in the Delaunay graph), and richness of the solution offered by teammates (number of links between the ball and teammates in the Delaunay graph).

Finally, occurrences of the analyzed tactic are located in the complete corpus of matches (zone 5). It is possible to display a two-dimensional representation of the Delaunay graph where the tactic’s edges are highlighted (zone 6), or to access video footage (zone 7). The expert can navigate within the complete sequence or from one occurrence to another (zone 8).

Numerous interactions between different parts of the visualization interface are available. Firstly, by selecting the tactic to analyze, a context transfer is made to the parts of the interface providing measures or visualization, ensuring coherent navigation. Navigation within tactics is dynamic through actions on priority order selection or tactic filtering.

It's also worth noting that the measures of interest used to sort tactics were just as useful for scrutinizing those that performed well as those that were unsuitable or had a low success rate. It was therefore just as possible to analyze the strengths and weaknesses of one's own team, as part of match preparation feedback, as it is to analyze the strengths and weaknesses of a future opponent.

Figure 6 presents in the observatory the analysis of the following tactic: [['28 Valentin Porte=Left Back_1'], ['Pivot=Left Wing_1']] which indicates a relationship being created between Valentin Porte and the opponent Left Back, then one pass later a relationship being created between the opponent Pivot and Left Wing. This pattern appears 22 times (support), and scores 6.33 times more than not scoring (*rho*), gives a favorable shooting position with a 63% chance of converting shots into goals (xG). This was a placed attack pattern, generally triggered 4 passes before the shot is fired. This pattern appeared in game sequences of around 14" and gives an average xG at the moment of the shot of 0.63 even with the pressure of 3 opponents on the shooter.

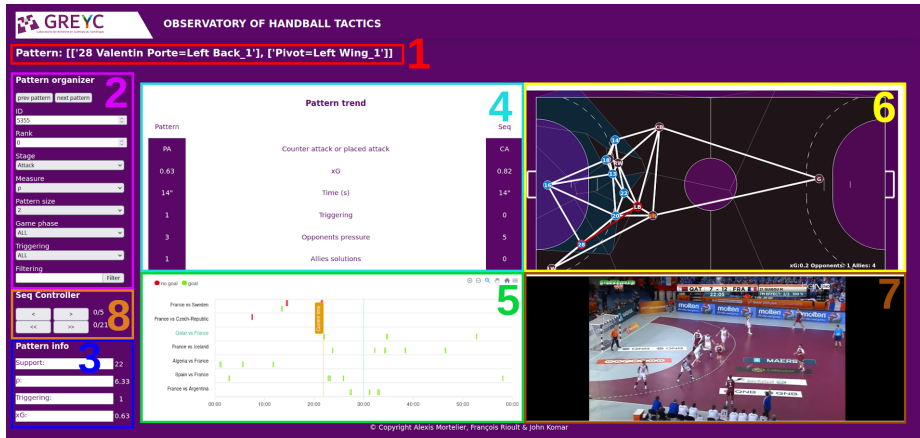


Fig. 6: Handball tactics observatory.⁵

5.3 Interest of the observatory for the expert

The tactics observatory helped identify recurring patterns in the highly dynamic sport of handball. This tool enabled to analyze the own style of play, to ensure that the match preparation was correct. It was intended to complement traditional video analysis, which was carried out by humans who made choices on the extracts and introduced numerous biases. The automatic analysis proposed here had the merit of being exhaustive and objective. The objectivity of the tactics

⁵ <https://morteli211.users.greyc.fr/observatory/>

displayed was enhanced by the accompanying prospective or retrospective measurement, which complemented the focus that a coach would like to give to his fetish tactics.

The observatory was also invaluable for understanding an opponent's tactics, both from the point of view of successes, which could be countered, and failures, which could be exploited or encouraged. Dynamic graphs potentially provided information on deeper aspects of the activity, which were not easily and at first sight accessible to a more traditional analysis.

6 Conclusion

In this article, we presented a method for designing an observatory dedicated to the tactical analysis of handball, implementing the use of dynamic graphs to visualize and study patterns of play. This approach added a temporal dimension to the exploration of game patterns, going beyond the simple snapshots that had been observed until now. By capturing the complex interactions between players, their trajectories on the court and passing sequences, this representation offered a better understanding of the dynamics of the game. Our choice of event-difference graph encoding provided the fine granularity essential for capturing changes in the structure of the dynamic graph. Using an approach based on the Voronoi diagram to create the relationships between players, we adapted this method to take better account of the specific topography of the handball court. This sequential graph structure then allowed us to extract recurrent tactical subsequences, which were evaluated according to measures of interest such as the emergence rate and the expected goal. These measures introduced a hierarchy of tactics, making it easier to navigate the observatory. The tactics discovered were then graphically illustrated in the observatory, providing coaches and analysts with a better understanding of the trends, strengths and weaknesses of the tactics employed.

For future prospects, it would be interesting to further explore the possibilities of integrating additional data, such as player physiological data or individual performance data, to enrich tactical analysis and offer deeper insights. In addition, extending this methodology to other sports could open up new avenues of research and enable enriching interdisciplinary comparisons. Ultimately, it would be advantageous to engage in ongoing collaboration with coaches and sports analysts to further develop and tailor this approach with a refined focus on UX design, thereby ensuring its applicability and effectiveness in the practical realm of handball and beyond.

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