Vote-Based Line Aggregation for Sports Field Registration

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***Abstract*—Sports field registration is the process of determining the area of a sports field in view of a video or image. This process underpins many technologies and opportunities for sports broadcasting, including game state reconstruction and virtual reality applications, leading to copious research in recent decades. In this paper, we describe an approach to sports field registration designed for Rugby League, and applicable to similar niche sports. Sports field registration is a field in which data is very expensive to annotate leading to a lack of methods that apply to sports without a large commercial influence. Our approach utilises simple Hough line detection techniques and builds upon their shortcomings to improve reliability. We use vote-based line aggregation - a novel approach to line-based sports field registration. Vote-based line aggregation takes as input the detected lines across every frame of a video and the homographies between these frames to generate a single set of field lines from which to generate a homography for registration. We show our method is significantly and consistently more effective than a single-frame Hough line detection method for registration and demonstrate how our approach solves regularly occurring issues in the field such as player occlusion and false positives. We also propose the extension of our method to further improve state-of-the-art deep learning segmentation methods.**

***Index Terms*—Homography, Sports Field Registration, Hough transform, Line detection**

I. Introduction

Sports field registration is the fundamental process in sports analytics and broadcasting, aimed at determining the exact location on the sports field that the camera is capturing [1]. By providing a spatial framework, sports field registration serves as the foundation for a wide range of applications, including gameplay analysis, statistical modelling, virtual refereeing, graphic overlays, and augmented reality for broadcasts [2], [3].

In the competitive landscape of modern media, sports broadcasters seek ways to stand out from their competitors by providing an improved viewing experience. Sports field registration methods allow these broadcasters to add insightful overlays to the sports field in real-time, allowing for a more enriched viewing experience for fans. An example of these applications is the 1st and ten yellow line system in American football which augmented the viewing experience by drawing a yellow line at the first down [4], [5].

Some sports leagues, such as the NFL, have turned to wearable tracking devices to monitor player movements [4]. However, these devices still require the grounding of the playing field boundaries to be able to add any enhancement to the sports broadcast.

For years, approaches to this problem have required manual annotation of frames in a video or an expensive calibrated multi-camera setup in sports stadiums to localize which part of the sports field is in view, and only in the last 10 years has this been achievable automatically. The most recent approaches to field registration rely heavily on large datasets, which are expensive to annotate [2]. Leading approaches in the field use edge map search approaches [6], [7], or deep learning methods to detect key points [1], [8] or lines [9] to establish a homography for registration. These methods fail when applied to niche sports with low data availability and/or without the presence of a stadium environment with a well-calibrated fixed camera.

This paper proposes **V**ote **B**ased **L**ine **A**ggregation (VBLA), an effective field registration method for Rugby League, a sport that faces the shortcomings of deep learning-based methods such as its low data availability and stadiums without expensive technology. VBLA uses the detected lines in every frame of a provided video to establish a consensus for the detected field lines, allowing for field registration without costly annotated datasets or deep learning models specific to a particular sport.

Despite many sports field registration applications not requiring real-time prediction, most recent methods focus on individual frame prediction [1], [4], [6]–[10] and neglect useful information in previous and future frames. We show in this paper that using the information gained from multiple frames in a sports video enhances registration accuracy and reliability.

This paper is organized as follows: Section II describes the VBLA algorithm and all other components required to generate a homography for registration. In Section III, we describe the experimental results. Section IV explains the limitations of our approach and proposes opportunities for its extension on other methods.

II. Proposed Approach

Sports field registration allows players and ball locations from a video to be projected onto a virtual sports field. This is usually achieved by finding a homography transformation that projects the field in a video or frame onto a simple field template or field coordinate system because most sports are played on planar surfaces. Estimating this homography is challenging because the correspondences between the features seen in an image and those in the field template are unknown and difficult to compute due to several factors, such as perspective variations, occlusion, dynamic scene elements, and lighting variations [11].

One approach similar to ours also uses image features to stitch together frames of the video to generate a panorama of the playing surface, where they use the outer border of the detected playing surface using pixel colour binning to establish the homography for registration [12]. This has the benefit of calculating a registering homography using all the information in the video. However, this method is bound by the requirement of seeing the entire playing surface in the video. This is not a common occurrence in many large field sports, where cameras rarely tilt low enough to see the nearest field boundary. Another method closely related to ours is described in [13]. In this approach, Hough transform line detection is applied on individual frames to detect a playing surface and iterate through every logical combination of horizontal and vertical lines, to identify the best correspondence. This approach uses all the information available on the playing field to predict the transformation but it is reliant on the Hough line detector successfully identifying at least two vertical and two horizontal lines in each individual frame.

In contrast, our approach overcomes the limitations of both methods. By projecting the detected field lines across all frames in a video, we show we can reliably generate a registering homography for each frame without the entire field being visible in the video and without requiring each individual frame to detect at least two horizontal and two vertical lines.

A. GBFIS Homography Estimation

As our approach uses the information gained from all frames in a video to generate the registering homography, we approach image stitching in a way that minimizes the computational load required whilst not limiting the format of the video stream to being from a single camera. To do this, we propose GBFIS (See Algorithm 1), an algorithm which finds the homography for each frame in the input, and stitches it to a starting frame. By stitching all frames in the video to the reference frame, we reduce the number of homography matrices we need to calculate for registration from n to 1, where n is the number of frames in the video. This significantly simplifies the problem.

Let $P = \{p_1, p_2, ...p_n\}$ be the set of Scale Invariant Feature Transform (SIFT) [14] features found for the set of frames $F = \{f_1, f_2, ...f_n\}$. Starting from some $i_s \in \{1, 2, \ldots, n\}$, we find all feature sets that have a sufficient number of matching features with p_{i_s}, $p_j \in P_f$, where $j \neq i_s$, and find the homography which projects each $f_j \in F_f$ onto f_{i_s}. We repeat this approach for each frame, which is stitched to f_{i_s} until all frames have been stitched together. To speed up this algorithm, we estimate the centre frame f_c using the lines detected with Algorithm 2 and set $i_s = i_c$. As GBFIS does not require the frames to be in order, footage from multiple cameras or camera angles can be registered at the same time and requires no tracking between frames.

Algorithm 1 GBFIS

Require: Start index i_s, pre-generated SIFT features P, all lines L, all frames F, minimum matches threshold τ_{min}

procedure GBFIS($i_s, P, L, F, \tau_{\text{min}}$)
- $H^c_{all} \leftarrow \{i_s : I_{3x3}\}$ ▷ Initialise Homographies centred on the start frame f_{i_s}
- $parents \leftarrow \{i_s : I_{3x3}\}$ ▷ Initialise $parents$
- $stitch\_options \leftarrow \{0, 1, \ldots, |F| - 1\} \setminus \{i_s\}$
- **while** $parents \neq \emptyset$ **do**
  - $parent \leftarrow$ pop$(parents)$
  - $i_p \leftarrow$ key of $parent$
  - $H_{\text{parent}} \leftarrow parent[i_p]$
  - **for** $idx \in stitch\_options$ **do**
    - $matches \leftarrow match(p_{i_p}, p_{idx})$
    - **if** $matches \geq \tau_{\text{min}}$ **then**
      - $H \leftarrow find\_homography(matches)$
      - $stitch\_options \leftarrow stitch\_options \setminus \{idx\}$
      - $H_{\text{new}} \leftarrow H_{\text{parent}} \times H$
      - $parents \leftarrow parents \cup \{idx : H_{\text{new}}\}$
      - $H^c_{all} \leftarrow H^c_{all} \cup \{idx : H_{\text{new}}\}$
    - **end if**
  - **end for**
- **end while**
- **return** H^c_{all}

end procedure

B. Vote-Based Line Aggregation

Our VBLA algorithm contains three steps: line detection, line projection, and line aggregation. These three steps allow us to consider the lines identified across frames and aggregate them into a single set of lines from which to estimate a homography for estimation.

1) Line Detection: The homography matrices allow us to find the connection between each frame, but the field lines are required to locate the connection between the image coordinate system and the field coordinate system. To detect these lines, we use Hough transform line detection [15] with Canny edge detection [16]. To ensure that votes are consistent between frames, we scale all frames F_f to be of size $(\mathcal{H}, \mathcal{W})$ and apply the Canny edge detector method to create the set of edge images $C_f = \{c_1, c_2, \ldots, c_n\}$. Let $(h, w) \in \{\{1, 2, \ldots, \mathcal{H}\} \times \{1, 2, \ldots, \mathcal{W}\}\}$ be the pixel coordinate, and $c_k(h, w)$ be the intensity of the pixel at location (h, w) on the edge map c_k for $1 \leq k \leq n$. We calculate the family of lines in polar notation[1] (ρ, θ) which could go through $c_k(h, w)$ if $c_k(h, w) = 1$. After repeating this process for each C_k, we take all lines of (ρ, θ) which have a sufficient number of votes as the detected lines for each frame and convert them to Cartesian representation $y = mx + c$.

2) Line Projection: While the lines detected from an individual frame are, in some cases, sufficient for field registration, they often do not provide enough information

[1] In the polar notation, ρ is the perpendicular distance from the origin to the line, and θ is the polar angle, the angle of the point from the positive x-axis.

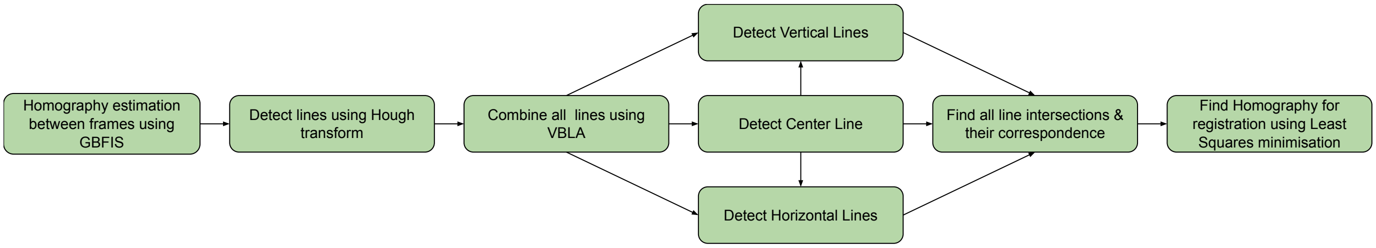

Fig. 1. Flow chart of the six steps required for registration for each frame.

Algorithm 2 Line Detection

Input: *image* f_x, *size*= $(\mathcal{H} = 270, \mathcal{W} = 480)$, *thresholds* $= (\tau_1, \tau_2)$, *min_votes* $= 100$, and *HoughLineDetector (HLD)*.
Output: Cleaned *cartesian_lines* and their *votes*.
procedure LINEDETECTION(f_x, size, τ_1, τ_2, *min_votes*)
  $result \leftarrow$ mask_background($image$)
  $player\_boxes \leftarrow$ remove_players($result$)
  $(\mathcal{H}, \mathcal{W}) \leftarrow$ dimensions of $image$
  $imS \leftarrow$ Resize($result, size$)
  $dst \leftarrow$ Canny(imS, τ_1, τ_2)
  for all $box \in player\_boxes$ **do**
    $dst[box] \leftarrow 0$
  end for
  $lines \leftarrow HLD(dst, \rho, \theta, threshold)$
    ▷ $\rho = 1$, $\theta = \pi/180$, and *threshold*=*min_votes*
  $cartesian\_lines \leftarrow$ Polar to Cartesian conversion
  $votes \leftarrow$ votes for each line
  return $cartesian\_lines, votes$
end procedure

for accurate registration, especially on a field as large as that used in Rugby League. To make up for this lack of information we utilize the lines detected in all video frames to generate a consensus for regularly detected lines. With a set of lines $L = \{l_1, l_2, ..., l_n\}$, and the set of homography matrices $H = \{h_1, h_2, ..., h_n\}$ which project each frame onto the starting frame f_{i_s} found with GBFIS, we can find the relative line set from the perspective of the start frame. Let the homogeneous point coordinates, where each line intersects the height and width of the input frame, be $P_f = \{p_1, p_2, ..., p_n\}$. We project p_i using h_i for $1 \leq i \leq n$. Combining the projected line sets gives the total set of detected lines L_t.

3) Vote-Based Line Aggregation: The combination of lines L_t returned from the projection operation tends to generate many duplicate, slightly offset lines, due to the imperfections of the Hough transform and the homography generated between frames using SIFT features. We reduce these duplicates using VBLA to take the vote-weighted average of each line to form a consensus. By taking the pairwise Euclidean distance between the start, end, and centre points of each line, we filter through the lines in vote order, creating a group of lines containing any other lines that have an average distance less than a threshold. Using these groups, we take the start and end points of the line using the vote-weighted average of the lines within the group. This algorithm, as outlined in detail in Algorithm 3, generates a single set of lines without duplicates, shown in Figure 2, which can be used to estimate a registering homography.

Algorithm 3 Vote-Based Line Aggregation

Input: Cartesian lines L_t, votes, image shape (H, W), threshold
Output: Scaled and sorted aggregated lines and their votes
procedure VBLA(L_t, votes, shape, threshold)
  Convert lines to start and end point. $line\_points \leftarrow$ Points($L_t, shape$)
$start\_points, end\_points \leftarrow line\_points$
$centre\_points \leftarrow$ mean of $start\_points$ and end_points
  Get line pairwise distances by Euclidean distance D
$d_{sp}, d_{ep} = D(start\_points), D(end\_points)$
$d_{cp} = D(centre\_points)$
$distances \leftarrow (d_{sp} + d_{ep} + d_{cp})/3$
$unprocessed \leftarrow \{0, 1, ..., |L_t| - 1\}$ ▷ Initialize unprocessed indices
$established\_lines \leftarrow \emptyset$ ▷ Initialize established lines
  for $i \leftarrow 0$ to $|L_t|$ **do**
    if $i \in unprocessed$ **then**
      $unprocessed \leftarrow unprocessed \setminus \{i\}$
      $sp_i \leftarrow start\_points[i]$
      $ep_i, \leftarrow end\_points[i], votes[i]$
      $v_i \leftarrow votes[i]$
      $line\_group \leftarrow \{sp_i, ep_i, v_i\}$
      for $j \leftarrow i + 1$ to $|L_t|$ **do**
        if $j \in unprocessed$ **then**
          $d \leftarrow distances[i, j]$
          if $d < threshold$ **then**
            $line\_group \leftarrow line\_group \cup \{sp_j, ep_j, v_j\}$
            $unprocessed \leftarrow unprocessed \setminus \{j\}$
          end if
        end if
      end for
      $established\_lines \leftarrow established\_lines \cup line\_group$
    end if
  end for
  Compute *WeightedAverage (WA)* for each line group
$average\_lines, average\_votes \leftarrow \{WA(line) \mid \forall\ line \in established\_lines\}$
$aggregated\_lines \leftarrow Cartesian(average\_lines)$ ▷ *Cartesian* conversion for the scaled points
  return $aggregated\_lines, average\_votes$
end procedure

C. Correspondences

The Rugby League field has lines that are often not visually distinct, leading to issues when finding the correspondence

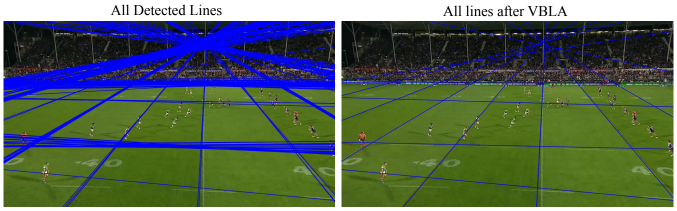

Fig. 2. Effectiveness of VBLA to remove duplicate lines. Lines are detected with $\tau_1 = 30$, $\tau_2 = 50$, $min\_votes = 100$ and aggregated with $threshold = 100$.

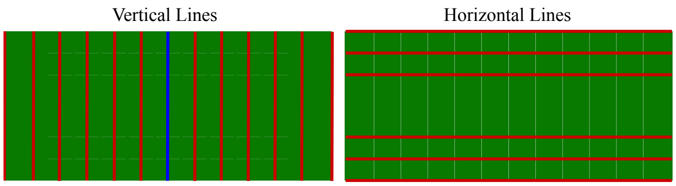

Fig. 3. Definition of Vertical and Horizontal Lines. Vertical lines correspond to the repeating 10-metre lines as well as the non-horizontal in-goal lines. Horizontal lines correspond to the sidelines and the dashed lines are 10 and 20 metres in from the sidelines. The field centre line is highlighted in blue.

between the detected lines and their true locations. We solve this problem by isolating the vertical and horizontal lines (illustrated in Figure 3) individually and finding the grid at which they intersect.

We detect vertical lines by utilising the camera geometry to our advantage. Since the camera recording the game is always in the stands, looking down at the field, all vertical lines on the field converge on the centre line. This allows the detection of vertical lines by finding pairs of lines that converge to the same point on the centre line. Detecting vertical lines with this method is robust to outlier vertical lines and also inherently finds the correspondence between each line and their true position on the field using their relative position compared to the centre-most line.

Horizontal lines are detected by estimating the centre-most frame in the video using the vertical lines detected previously. This is done by taking the votes of vertical line pairs and the line onto which they converge for each frame in the video to find a consensus of the centre-most line. We take the frame where this line appears most vertical and centred to detect the perspective from which we can detect the horizontal lines. Because we remove the crowd and isolate the field before detecting lines, we assume the topmost line detected is the far sideline of the field. Other detected lines have their correspondence matched based on whether they are closest to the farthest sideline or the closest sideline, and assigned according to their vertical location.

D. Registration

With a set correspondence between detected lines, we take all the intersections to create a grid of coordinates containing every intersection location. We use Direct Linear Transformation (DLT) [17] to perform least squares minimisation and find the optimal homography, which maps each detected

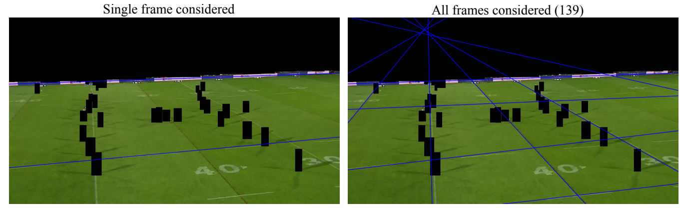

Fig. 4. Player Occlusion Robustness. Projecting aggregated lines across frames allows for the detection of 6 additional lines from the perspective of this frame.

intersection point to the corresponding intersection in the field template. This registering homography can then be applied to all frames in the video using the results from GBFIS.

III. Results

We have conducted our experiments on clips one frame per second taken from NRL Rugby League games, with testing also on regular television broadcast clips. All images were 1080×1920 in dimension, and we have assumed the field dimensions to be $68m \times 116m$, the standard size for the NRL [18].

All model parameters remained constant between all experiments with no input from the user. Given the lack of manually labelled data, our experiments focus on the improvements our model has over single-frame registration and present evidence of our method's viability in the form of registered images 7. We evaluate the ability of our approach to remove outliers and handle field occlusion by players, as well as the improvement in reliability and accuracy of our model in contrast to using individual frames to generate a field registration.

To generate interpretable metrics, we analysed 20 three-minute clips at one frame per second (180 frames total). These clips were chosen randomly throughout the raw footage to avoid bias influencing results. For our metrics, we analyse the proportion of frames that are capable of being manually registered, being frames that feature at least two horizontal and two vertical lines. We also analysed the proportion of frames that could be automatically registered, which our method could process and register without supervision.

A. Player Occlusions

Player occlusions often lead to difficulty detecting key lines or points in sports registration methods, making registration a challenging problem [8]. When utilising our method using individual frames only, player occlusion results in many crucial lines being missed in the calculation. In our experiment of 20 random clips from raw footage, we found only 14.9% of frames had sufficient lines to be manually registered when analysing the lines detected for an individual frame. In Figure 4, we demonstrate the effectiveness of line aggregation to account for player occlusion. Our method can project lines from external frames once players have moved from the path of occlusion to improve the reliability of the method to detect adequate lines to generate a field registration.

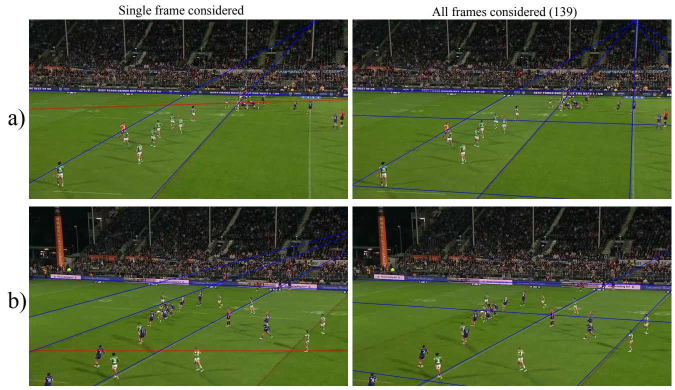

Fig. 5. False Positive Removal. After VBLA false positive lines are either adjusted for by other lines (a) or removed due to a lack of votes (b)

B. False positive removal

Line detection using the Hough transform is especially susceptible to false positives [13]. In the same vein as player occlusions our model is robust to false positive lines due to the voting nature of the algorithm. By taking votes from all frames in a video we either correct for the influence of the point through the weight of other similar lines with agreeing votes, or the false positive line is entirely removed by not being sufficiently strong to be kept. As an example, in Figure 5.a, the line has an influence on the inner 10-metre line but is overwhelmed by the votes of other frames in the clip leading to its removal. Figure 5.b demonstrates the false positives' entire removal by not having enough frames that agree with it.

C. Improvement above single frame registration

To establish the extent to which our vote-based method improves upon an individual frame line detection method, we examine the effectiveness of our method at generating homographies for registration for 20 randomly chosen clips from Rugby League matches. Our experiment evaluates the proportion of frames that can be manually registered, meaning there are at least two detected horizontal and vertical lines that would require manual annotation for a homography, and the proportion of frames that can be automatically registered with no user input.

Our experiment found among 20 random three-minute clips at one frame per second, 12 clips were able to be automatically registered. The results show that VBLA was capable of generating information for manual homography detection in 100% of frames across all 20 clips, whereas single-frame methods were only capable of registering 14.9% of frames with manual input. We also find that within the 20 clips experimented on, 12 were able to be manually registered without user input, and within these 12 clips, 99.2% of frames were capable of automatic registration, with the remaining 0.8% being unable to be stitched to the remaining frames in their respective clips. Within these 12 clips, we also found single frame line detection was able to automatically register 0.2% of frames, with an additional 17.4% being manually registerable.

TABLE I
COMPARISON OF REGISTERABLE FRAMES FROM VBLA APPLICATION ON SINGLE FRAMES AND ALL FRAMES

Automatic Registration	Single Frame		All Frames	
	Manual	**Automatic**	**Manual**	**Automatic**
Yes	17.6%	0.2%	100%	99.2%
No	10.8%	0%	100%	0%
Total	14.9%	0.1%	100%	59.5%

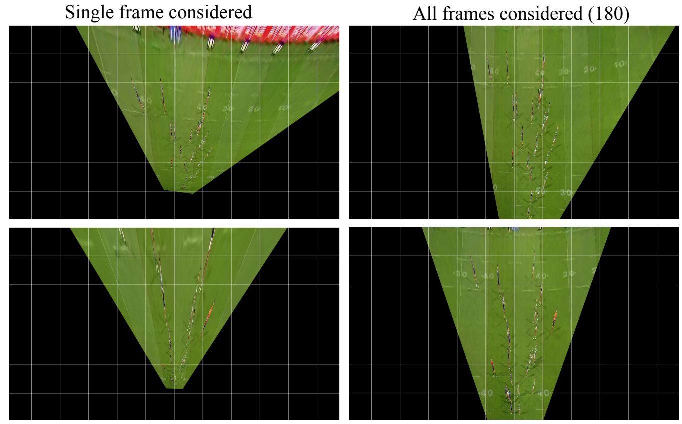

Fig. 6. Registration comparison between VBLA on an individual frame and VBLA on all frames in a three-minute clip. Single frame application is heavily influenced by false positives and undetected lines

Beyond there being large improvements in automatically stitchable frames with VBLA, we find the quality of registration improves significantly on average with more information utilised to generate the registering homography. A common issue with sports field registration methods is the tendency for the model to generate a valid homography for registration close to the detected lines or features [10], but have this homography not be valid for the remainder of the field, leading to warping further away from the area within frame. This effect is particularly noticeable in Figure 6, where we can see the frames registered using the information from a single frame tend to have a good quality registration in the centre of the field, which deteriorates further away from the centre we look at. Using VBLA, this is not as significant of an effect, given lines from the remainder of the field are considered even when registering a frame with little information present.

IV. LIMITATIONS AND FUTURE WORK

A. Limitations

While our approach has shown to be significantly more reliable than the single frame alternative using field lines for homography detection, it is limited in its applications. One of these limitations is the fact that vertical lines are much more reliable to detect than horizontal lines given an unknown camera position 6. Another limitation of our method is it is strongly reliant on detecting the field's vertical centre line in a clip. Both the vertical and horizontal line detection formats

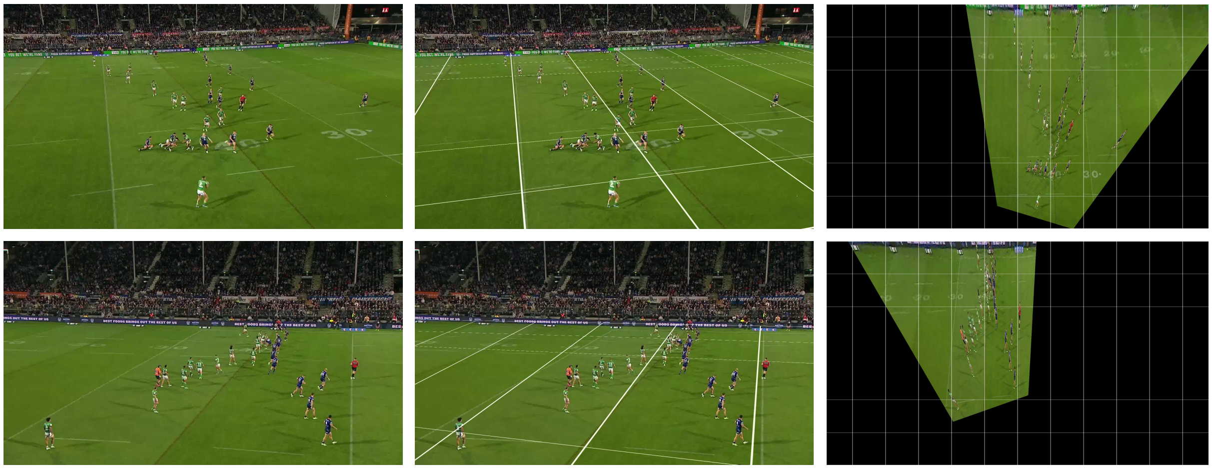

Fig. 7. Registration results. GBFIS applied with $\tau_{\text{min}} = 80$, VBLA applied with $\tau_1 = 30, \tau_2 = 50, min\_votes = 100, threshold = 100$.

discussed in this paper rely on detecting the centre line to detect the line that vertical lines are converging to, and to determine the perpendicular horizontal lines. This makes clips without a detected centre line unable to be registered automatically. Lastly, the method is restrained by the data input to the model. Image stitching frames that have a scoreboard featured in a static location, for instance, often require preprocessing to prevent incorrect stitching.

B. Future Work

We have shown the strengths of using collaboration between frames of videos to enhance the quality and reliability of homographies for registration using a simple Hough line detection method. We anticipate that similar improvements could be seen utilising vote-based aggregation among state of the art deep learning methods. Deep learned models that use segmentation to detect lines [9] or key points [8] could likely improve their methods using vote-based aggregation to stabilise prediction. In general, the field of research has been extensively focused on single-frame prediction, leading to few efforts to extrapolate information from other frames to enhance video-wide predictive performance—despite a large proportion of use cases being on recorded video.

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