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Real-time multi-sport action tracking with convolutional neural networks

Axel Baldanza^{1,2,*}, Jean-François Aujol², Yann Traonmilin², and François Alary¹

¹Rematch

²Univ. Bordeaux, Bordeaux INP, CNRS, IMB, UMR 5251,F-33400 Talence, France.

*a.baldanza@rematch.fr

Abstract—State-of-the-art localization and action tracking methods have shown bad performances on amateur sports videos due to the variability of acquisition conditions and occlusion problems. Moreover these methods need to be modified in order to be applied to different sports. In this paper, we present a real-time computable method that allows video action tracking in amateur sports. This method uses a convolutional neural network to analyze the players' movements instead of basing the tracking on object detection. This feature allows it to be transposed out-of-the-box to different sports.

I. INTRODUCTION

Tracking methods in sports is a subject that has been growing in importance in recent years. In this paper, we aim at designing a method for tracking the action on the field by predicting global camera motions. This method aims at learning and reproducing how humans film sports. Successful global motion tracking could then be used to design automatic camera systems that manage to follow the action. We focus here on the context of amateur sports. This context has the particularity to defeat many state-of-the-art methods because of its variability (global setting, point of views, type of cameras).

One way to track the action is to follow the ball. Methods in the literature that aim to detect and track the ball such as [1], [2], [3] are efficient for the professional context. The images studied in this type of method make the detection simpler. The camera is located much higher with respect to the field and avoids ball occlusions. Many of these methods are developed for soccer only, where the contrast between the color of the ball and the grass is sharp and the ball is often dissociated from the players, which makes it more easily detectable. These algorithms show difficulties on sports like basketball and handball where the ball is mainly held by the players. [4] looks at the performance of state-of-the-art object detection methods to detect the ball on amateur videos and highlights the difficulties of this algorithm to localize the ball in this context. As explained in [5] some of these methods show unusable results on our test database and tracking the action by detecting the ball proved to be impossible. State-of-the-art real-time object detection methods such as YOLO (You Only Look Once) architecture [6], [7] and Faster R-CNN (Region-Based Convolutional Neural Network) [8], [9] pretrained on COCO dataset [10] failed to detect balls in more

than 95% of the frames. A paper such as [11] presents a multi-sport ball tracking method, including sports where the ball is hand-held. However, the pipeline of this type of method is too computationally expensive to be used in real-time on embedded systems, particularly because of the precise and complete tracking of all players it requires. In the same way, some papers on tracking in sports as [12] present methods that are based on the combination of object tracking and remapping in a field plane. Remapping on a field plane is an efficient method to allow complex tracking in sports. However, these methods are also too computationally expensive in our conditions. Another way to locate the action is to localize and track the region of interest in the videos. The state-of-the-art methods for spatio-temporal action localization focus on images containing only a small number of salient objects. The videos considered in [13], [14], [15], [16] show that only a few objects are present in the images. This feature makes the localization of the action in the image easier. Our images have a large number of people and this type of algorithm is hardly efficient in our conditions. In [5], it is shown that action tracking in basketball can be done by predicting the action global motion instead of classic spatial localization. Assuming that player displacements could induce camera motion, computing optical flow in sports videos can give robust information on the position of the region of interest. This way of tracking the action allows us to avoid non-robust detection in a degraded recording context. This method is also designed to reduce the computational complexity compared to the methods mentioned above. This feature enables it to be used in embedded solutions in real-time. The method presented in [5] has shown very encouraging results. However, to be efficient, this method requires a separation of the model into different situations. Its success is thus very dependent on the classification of the action into different situations. This model has shown limitations in its ability to track long sequences and to fit some sports other than basketball where camera motions are linear and the classification of situations was complex.

A. Our method

The method presented in this paper is based on previous work [5]. We predict the camera motion using a convolutional neural network. The use of the neural network enables us to avoid the classification of situations used in the piecewise

linear model from [5] and to integrate it directly into the prediction model with a larger number of trained parameters. The objective of this improvement is to make the model more accurate and more adapted to the problem while remaining fast to compute. This should allow the model to be extendable to long sequence videos and other sport context. Our new method is tested on basketball and handball videos. The model takes as input a sport video, computes the segmented optical flow of the foreground at each frame, and passes as input to the convolutional network n frames with a gap of k frames to add a temporal analysis. The algorithm returns the camera displacement necessary to track the action in the following frame.

B. Contribution

The main contribution of this paper is to propose an accurate tracking method that is robust to most of the variations induced by the amateur conditions. Moreover this method can be transposed out of the box to several different sports, just by re-training the network. This is one of the limitations of state-of-the-art tracking methods in sports based on object detection compared to our method. The way this model is designed and its architecture allows to compute the tracking in real time on embedded solutions, whereas methods based on object detection are often slow and computationally expensive. The prediction of the global camera motion also allows the automatic labelling of the database while the annotation of the databases for object detection is time consuming.

II. GLOBAL CAMERA MOTION PREDICTION METHOD WITH CONVOLUTIONAL NEURAL NETWORKS

In this part, we describe a method for deducing global camera motion from optical flow using convolutional neural network.

A. Problem formulation and previous prediction model

We recall the formulation of the problem from [5] which is the basis of this work. Given a video, the method segments foreground and background by setting to 0 all the optical flow [17] elements close enough to the 2D median (u^*, v^*) of the optical flow. The optical flow of the foreground is defined as the matrix $F^t \in \mathbb{R}^{N \times M \times 2}$ composed by elements $f_{i,j}^t$ defined as

$$f_{i,j}^t = \begin{cases} (u_{i,j} + u^*, v_{i,j} + v^*), & \text{if } (i, j) \in \Omega. \\ 0 & \text{else .} \end{cases} \quad (1)$$

where $\Omega = \{(i, j); \|(u_{i,j}, v_{i,j}) - (u^*, v^*)\|^2 \geq \theta\}$, $(u_{i,j}, v_{i,j})$ is the result of optical flow estimation at position i, j . and θ a threshold. Set like this, we assume that the background displacement defines the camera motion and that the foreground motions corresponds to the motion of the players. Non-zero elements of the foreground are added to (u^*, v^*) to make the foreground values independent of the camera motion.

In [5], a piecewise linear supervised learning model to predict global camera motion is described. This model uses a learned weight matrix z_s for each situation (e.g. left team

attacks on the right, right team attacks on the left, ...) occurring in the videos to predict camera global motion from the segmented optical flow of the foreground

$$d^t = \langle f^t \eta, z_s \rangle + e^t, \quad (2)$$

where $d^t \in \mathbb{R}$ is the motion predicted, $f^t \in \mathbb{R}^{NM}$ the flattened vector of segmented horizontal optical flow defined as in (1), $z_s \in \mathbb{R}^{NM}$ the learned vector for each situation, $\eta \in \mathbb{R}^{NM}$ a normalization vector, and $e^t \in \mathbb{R}$ the noise. This model needs a robust situation management algorithm to use the right matrix for what is happening on the field. This task can be challenging during long sequence videos, this is why this model has shown difficulties to track action in long sequences. Evaluation of this method shows accurate performances on short basketball videos but it starts to show bad results on long sequences and other sport videos.

B. 3D-CNN architecture for action tracking

We propose the following network architecture to predict global motion: the model takes as input n foreground optical flows computed with intervals of k frames to add a temporal dimension analysis to the network, and it outputs a prediction of the camera motion at time t . The gap k between the inputs and the number n of optical flows can be adjusted according to the needs of each sport. In our case, k and n were chosen experimentally to maximize the performance. We used $k = 10$ and $n = 3$ for both basketball and handball videos. This allows the model to use the evolution of players' motion across time to improve performances as it can adjust its prediction with respect to what happened previously. This also makes it more robust to the variations of amateur sport videos. To improve the calculation times, we were able to downsample the input frames to 160×90 while keeping the same performance. The architecture of the network is summarized in Table I.

Block	Layers	output size
Conv1	Conv : 3×14 3x3 filters Maxpool : 2x2 filter	(32, 90, 160)
Conv2	Conv : 64 3x3 filters Maxpool : 2x2 filter	(64, 45, 80)
Conv3	Conv : 128 3x3 filters Maxpool : 2x2 filter	(128, 22, 40)
Conv4	Conv : 256 3x3 filter Maxpool : 2x2 filter	(256, 11, 20)
FC1	FC : 128x11x20	(1,128)
FC2	FC : 128x64	(1,64)
FC3	FC : 64x32	(1,32)
FC4	FC : 32x1	(1,1)

Table I: Network architecture: This table shows the components of our motion prediction network and the different sizes of output for horizontal flows of size 90x160. The input is processed by 4 convolutional layers Conv1, Conv2, Conv3, and Conv4 producing convolutional feature maps. Then the result is flattened to pass through 4 fully connected layers (FC1, FC2, FC3, and FC4).

The architecture and the number of parameters have been chosen to avoid overfitting and to be computed in real-time

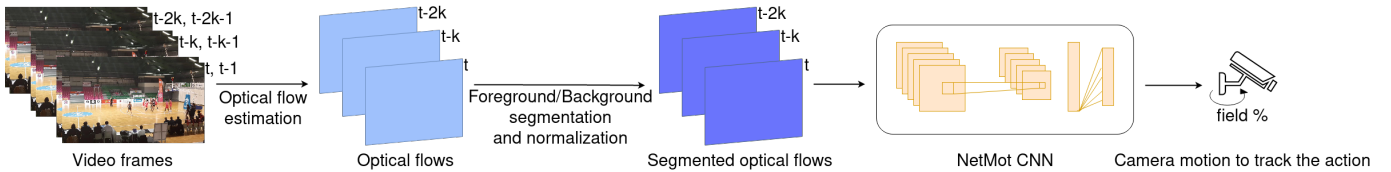


Figure 1: Detailed pipeline of the proposed algorithm.

by embedded solutions. It can be applied in real-time as soon as the acquisition time exceeds $(n-1)k$ frames. In this sense, our network allows provides good accuracy (see experiments) while remaining very fast to apply. On common laptop CPUs, the output is calculated at 70,5 fps. It can be calculated in real-time for classic video qualities but also for very high-quality solutions thanks to the downsampling. This is an advantage of not performing complex object detections. Figure 1 shows an illustration of our proposed pipeline to summarize and understand how the method works. The output of the network is the predicted camera motion normalized in a percentage of the field.

With this method, we can predict both vertical and horizontal motion. However, in the sports studied here, the vertical component did not add value as the whole height of the field is captured within one frame. This is why we predict only the horizontal motion in the following. For other sports, the model can easily be adapted to 2 dimensional optical flows if the vertical component has to be analyzed.

C. Training and dataset

The evaluation is performed on videos from two sports: basketball and handball. As the two sports require different behaviors, we used two training databases (60494 optical flow matrices for basketball and 42654 for handball). Videos from these databases match the constraint that the camera is placed close to the middle of the field to make our model consistent. The networks are learned using ADAM [18] optimizer.

As explained in [5], the main advantage of this work is that databases can be annotated automatically. The camera displacement is calculated as the 2D median of the horizontal optical flow assumed as the background global motion calculated at time t . The motion to be predicted is then annotated with this value, normalized as a percentage of the total field. The normalization helps to reduce the subjectivity and variability of the labels between the videos. Finally, the consistency of the annotation has been checked manually for each video in the database.

III. EXPERIMENTAL RESULTS

In this section, we study the effectiveness of our optical-flow-based method for tracking interesting content in sport amateur games. Here, we will compare the method presented in this paper (NetMot) with a version of the CNN that takes as input a single segmented optical flow computed at time t (NetMotV0) to show the benefits of the addition of temporal dimension analysis, and the method presented in [5] (PEN).

To the best of our knowledge, there is no other out-of-the-box method in the literature that allows this type of prediction. Furthermore, the tests of the state-of-the-art real-time object detectors on our database have given too imprecise results to track the match thread in any video. Performances are evaluated on 3 different test datasets labelled with the same methodology as the training datasets. First, to compare our model to the PEN model, on short basketball videos, we tested it on the 15 basketball videos presented in the paper [5]. To evaluate the ability of the model to track long sequences, we tested it on 7 basketball videos ranging from 24 seconds to more than two minutes. Finally, to evaluate the adaptation to another sport, we also evaluated the model on 14 handball videos.

A. Evaluation metrics

To evaluate the numerical results of the model, we use the mean absolute error (MAE) between motion predictions and the ground truth and the MAE between predictions and ground truth integrated with respect to time (i.e. position with respect to the start of the video). We are analyzing time integration of prediction results because it highlights the shift between the position of the predicted camera tracking at time t and the ground truth. We call this metric "Tracking Error" and we consider that when it is over 15% of the field, the algorithm has lost the location of the action. On long videos, we also need to analyze the MAE on sub-sequences of 10 seconds to make sure that the camera never loses track of the match before recovering it. The section MAX TE (Max Tracking Error) corresponds to the maximum MAE computed on 10-second subsequences. Analyzing MAE on standard prediction allows us to see if predictions are locally close to ground truth. However, a model can have predictions closer to the ground truth but a less accurate tracking, because of drift and compensation phenomena.

B. Evaluation results

The evaluation results on the test databases show that NetMot is more accurate than the PEN model. Focusing on the standard predictions, we see that the MAE is significantly lower for NetMot. 80,6% of videos have lower MAEs with NetMot than with PEN. This result means that the model predicts displacements that are closer to the ground truth. It means that the model uses less compensation to keep track of the game. This makes the global motion of the camera smoother for the viewer. Looking at the Tracking Error, we see that NetMot is more accurate than PEN across time too. Again, 80,6% of videos have a lower Tracking Error with

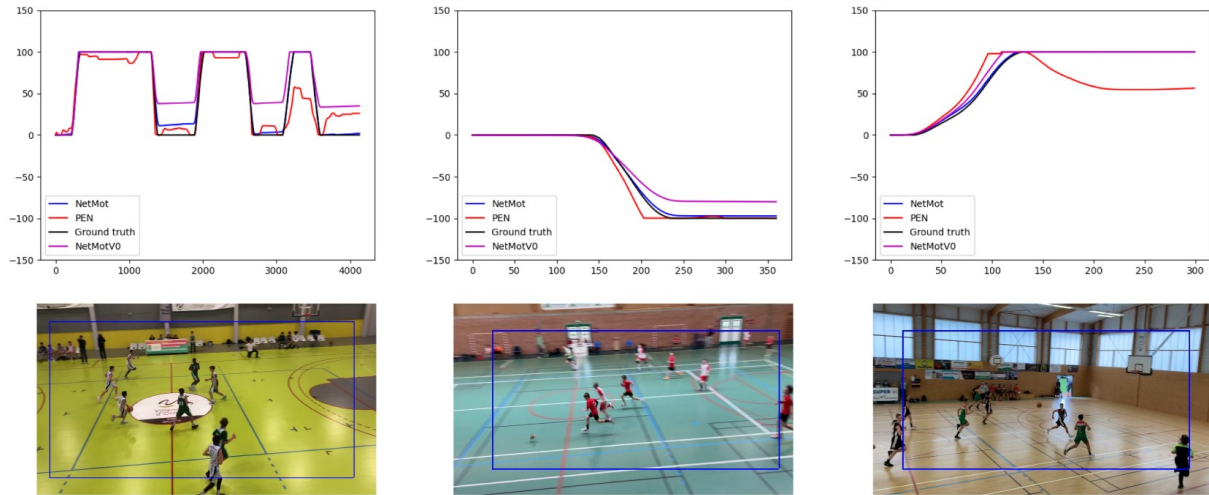


Figure 2: Examples of well-tracked videos from long basketball sequence (left), handball sequence (middle) and short basketball sequence (right). The blue box shows the position of the (virtual) camera using our tracking method.

	MAE			Tracking Error		
	PEN	NetMotV0	NetMot	PEN	NetMotV0	NetMot
MEAN	0.18	0.11	0.07	12.04	7.15	4.06
BEST	3	6	6	2	6	7
NUMBER OF MAE >15				3	4	1

Table II: Summary of the performance of the different algorithms on the short basketball videos database. Mean absolute error on motion prediction (MAE) and Tracking Error with the two versions of the model (NetMot and NetMotV0) and the model presented in [5] (PEN). NetMot provides the best results.

NetMot than PEN. Performances on short basketball videos are summarized in Table II. In this database, the average MAE is significantly lower for the new model. This means that the camera position is on average closer to the ground truth. The action is better centered and the loss of the game thread is less likely. These results show that using a convolutional neural network with an increased number of parameters compared to the PEN model and adding temporal dimension enhances the precision and robustness of the model.

The tracking error of the PEN model on the short basketball test database is higher than that presented in [5]. This result is explained by the fact that in the present work, this model is trained on a larger and more varied database. These results highlight a lack of flexibility of the previous model [5] that has difficulties adapting to more varied data.

Comparing NetMot with the NetMotV0 network, we can see that the addition of the temporal dimension in the inputs increases the accuracy of the network both in terms of mean tracking error and in terms of videos where tracking failed.

The results on short handball videos presented in Table III show that the NetMot model is the most accurate method across time for this sport too. It was able to track the actions of all the videos in the test database without losing the

Video	MAE			Tracking Error		
	PEN	NetMotV0	NetMot	PEN	NetMotV0	NetMot
1	0.21	0.11	0.08	4.92	10.03	5.68
2	0.31	0.13	0.11	10.68	17.86	10.79
3	0.10	0.06	0.11	14.04	3.14	5.31
4	0.1	0.07	0.16	4.02	3.68	2.99
5	0.19	0.05	0.29	9.27	3.97	9.09
6	0.15	0.13	0.1	4.82	21.53	11.6
7	0.1	0.07	0.08	5.14	12.66	2.61
8	0.26	0.08	0.17	9.36	7.96	5.49
9	0.14	0.1	0.1	2.97	20.45	6.27
10	0.15	0.12	0.13	6.17	22.35	11.22
11	0.24	0.06	0.11	9.65	13.3	6.62
12	0.22	0.09	0.1	7.02	10.43	2.71
13	0.14	0.05	0.12	4.1	8.25	2.8
14	0.15	0.08	0.07	4.80	13.13	0.57
MEAN	0.18	0.08	0.12	6.92	12.05	5.98
BEST	0	11	4	5	2	7
NUMBER OF MAE >15				0	4	0

Table III: Mean absolute error on motion prediction (MAE) and Tracking Error with the model NetMot on handball videos. The table shows that our model NetMot tracks the action on short handball sequences without losing the match thread (Tracking Error ≤ 15).

location. The NetMotV0 method obtained more accurate local prediction but it was much more prone to the drift phenomenon and it obtained much worse results across time. Again, these results highlight the interest in using the temporal component for prediction. The PEN piecewise linear method showed accurate results for tracking handball videos. However, the results are on average significantly less accurate than those obtained by NetMot.

The performances of the method on long sequences are presented in Table IV. These results and the curves presented in Figure 2 show that NetMot can follow long sequences of matches without losing the action. To be consistent with the evaluation metric, and to know if the algorithm has lost track of the game during the sequence, we study the MAE on 10-

Video	Duration	MAE		Tracking Error		MAX TE	
		PEN	NetMot	PEN	NetMot	PEN	NetMot
1	0:34	0.15	0.09	6.67	2.42	10.69	3.76
2	0:24	0.001	0.003	0.05	0.005	0.057	0.005
3	2:18	0.1	0.07	14.14	0.03	45.86	12.58
4	0:30	0.001	0.004	0.11	0.01	0.12	0.009
5	1:42	0.12	0.04	23.08	5.68	39.50	8.87
6	0:53	0.16	0.07	11.21	4.44	17.72	10.83
7	0:56	0.14	0.08	24.15	4.64	53.82	9.24
	MEAN	2.93	0.04	11.34	2.46	-	-
	BEST	2	5	0	7	0	7

Table IV: Mean absolute error on motion prediction (MAE) and Tracking Error with the model NetMot on long videos. The table shows that NetMot tracks the action on long sequences without losing the match thread (MAX TE is always ≤ 15).

second sub-sequences. In this database, Table IV shows that no 10-second subsequence has been tracked with an MAE higher than 15% of the field. This table also highlights the improvement that convolutional neural networks brings over the piecewise linear method PEN. We observe that the biggest limit of the PEN method [5] is its failure to track long sequences adequately. The results of PEN on long videos show that this method lost the position of the action several times. These results show that the method NetMot introduced in the present paper is robust to long game sequences.

The results presented in Figure 2 show how the Netmot model (blue curve) is able to predict values close to the ground truth (black curve) compared to other models. The number of frames is different between short and long sequences. This explains why the transitions look sharper on the curves associated with the long sequences. On the images, we can see that the sequences are well tracked by the algorithm because the blue rectangle is not shifted from the capture camera. This means that the predicted camera has followed the same motion as the real camera.

IV. CONCLUSION AND FUTURE WORKS

In this paper, we presented a method based on convolutional neural networks to track the actions of various amateur sports in real-time. This method differs from other state-of-the-art methods by several points. First, it is reusable out of the box in several sports. The use of player movement analysis rather than precise object location makes it robust to non-professional conditions. The automatic annotation of the training databases also allows a significant time saving compared to methods where the position of objects in the images is necessary for the training. Finally, the low computational cost makes it possible to compute the tracking in real-time on low computational power embedded processors. Our method has shown very good results in its ability to track actions. It is able to track actions in several different sports as well as long sequences of matches. However, in real conditions, losing the thread of the game can lead to real difficulties to find it quickly. Designing a tracking method based on player movements in amateur videos captured with a wide-angle camera could help limit this factor.

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