A GIS-Centric Optical Tracking System and Lap Simulator for Short Track Speed Skating

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***Abstract*—This paper presents a GIS-centric computer vision system for tracking high-speed skaters in competition and training situations. This system outputs spatio-temporal trajectories that are analyzed through presented geometric, physical and power-based models in order to evaluate sports performance. Through spatial SQL and shared database access, the GIS enables the manipulation of the trajectories and offer, amongst other, selection, fusion and completion of tracks, as well as automatic computation of distances between competitors. We propose a new method for (1) calibrating the cameras using a GIS-like image rectification method; 2) simulating trajectories and their associated power profiles to model the sport's domain; 3) incorporating the instant center of rotation in both the particle filter's dynamic model and the simulator and 4) leveraging several GIS advanced capabilities in a client-server application. Experimental results show that our rectification methology is very precise, that our tracking performance is acceptable and that the proposed power balance model is very close to the state of the art.**

***Keywords*-tracking; camera calibration; segmentation; image rectification; GIS;**

I. Introduction

This work aims to automatically track the movement of speed skaters on an indoor ice rink and to present this data in a comprehensive and synthetized way to coaches. From the computer vision point of view, several problems present themselves: partial occlusions when skaters are very close to each other; the size of the skaters range from about 20 by 20 pixels to 50 by 50 pixels; skaters are often tracked simultaneously in two or more cameras; the calibration of the cameras in such a large area. From a user-centric point of view, the problems are related to the usability of the system; manipulation, correction and management of the data series; potential integration of external systems; creation of simple yet useful tools to assess performance from trajectories.

The remainder of this paper is organized as follows: the next section explore the related work in sports. Section II is the overview of the proposed system. Section IV explains the camera calibration is carried out using GIS-style image rectification. Section V describes the tracking method based on particle filtering and introduces the notion of instant center of rotation as a part of the dynamics model. Section VI shows the geometric and power balance models of simulated data that provides a basis for human performance assessment on real data. Results of the tracking module are given in section VII. A short discussion is presented in section VIII before the conclusion of this paper.

II. Related work

There are several documented uses of video analysis systems in sports. Early annotation-based systems were conceived to analyze, amongst other, team plays, basic motions and techniques, position on the field, speed or acceleration. Barris and Button [1] identifies several applications of these systems, notably the planning of tactics and strategies, the measurement of the team performance and intervention efficiency, as well as the access to an early cinematic retroaction. The major challenges cited are the large raw data volume and the extraction of pertinent and reliable information. Vincent [2] lists several data mining and aggregation scenarios in various sports context.

The position of the athlete on the field can be obtained by force plates, timing gates and wireless tags. For outdoor sports, GPS receivers and inertial measurement units (IMU) are often key elements [3], [4], [5]. For indoor sports, optical tracking systems are often used. While systems relying on markers are generally more precise, international regulations often prohibit any modification to the equipment. Several optical-based implementations exists for skating and in large array of related sports [6], [7], [8], [9], [10], [11], [12], [13].

Using tracking data and video analysis, several models can be devised. Van Ingen Schenau [15], [16] estimates the friction forces of the air F_{air} [17], [18] and of the ice F_{ice} [19]. By using the power balance assumption, De Koning [20], [21], [22] computes the optimal distribution of work for cycling and 1500 meters speed skating. Efficiency and energetic costs leading to optimal race conditions can also be modeled by taking in account average power per stroke or the overall technique [23], [24], [25], [26], [27], [28].

III. Overview of the system

The system is based on a star network of four GiGE Prosilica GC650 cameras delivering 25 VGA frames per second. The acquisition server launches four separate asynchronous threads to store the uncompressed grabbed frame

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on disk. A Omron CQM1 programmable logic controller programmed in Ladder insures that all cameras are synchronized by outputting a +/- 5V level on the camera input pin to start or stop the data acquisition. In this fashion, all sequences on disk contain the exact same number of frames.

Once saved on disk, the user can send requests for post-processing to the server using a dedicated client application. The four video sequences may be realigned and compressed to a single, smaller, more manageable file. The other main data processing is the particle filter optical tracking which produces a series of localized detections called tracks. All along those steps, intermediate results are stored in a centralized database linking the skating event and its competitors to the video sequences and extracted tracking data.

The client application offers the possibility to drill down in the database to select an event and playback its video sequence. Manifold, a commercial geographical information system (GIS) enables the manipulation of the associated tracking information. It holds as a base layer an orthographic referential closely duplicating the official skating rink of the ISU. By the mean of spatial SQL scripts and native capabilities, the GIS offer, amongst other, selection, fusion and completion of tracks, automatic computation of distances between competitors.

Most user-centric use cases covered by the present system were related to data acquisition, visualization, manipulation and management. These aspects were addressed as a mapping problem. The GIS was used to host a wide array of functionalities, including pan and zoom, aggregation and edition, free-hand measurement, track fusion, thematic formatting, labelling, and geospatial database interoperability. Equipped with this toolbox, processed trajectories can be more easily analysed according to their trajectories and underlying dynamics.

The trajectories alone are not sufficient to assess the performance of the athlete. A better basis is the power deployed as it reaches several disciplines of sports science. A non-accelerated parametric lap simulator, programmed in Matlab, completes the system and is presented in section **??**.

IV. Camera calibration

The ice rink dimension is 200 feet by 100 feet. Lenses were chosen to cover a rectangular field of a view mapping a little more than a quarter of the ice surface, resulting in a field of view of about 44 meters. A 10% overlap zone is present between the field of view of each camera. The height of the structure housing the cameras of 68 feet, or about 22,5 meters, constitutes the distance to the subject. Sony's ICX424AL CCD sensor possess 659 effective pixels, each measuring 7,4 microns, for a total CCD size of 4,88 mm. Using the lenses Equation 1, the resulting focal distance is 3,2mm for a distance of 68 feet.

$$f = \frac{CCD \times distance}{width} \tag{1}$$

Zhang [29] camera calibration method was first considered. This method employs the pinhole camera model. By observing a checkerboard pattern under different orientations, the intrinsic and extrinsic parameters are computed.

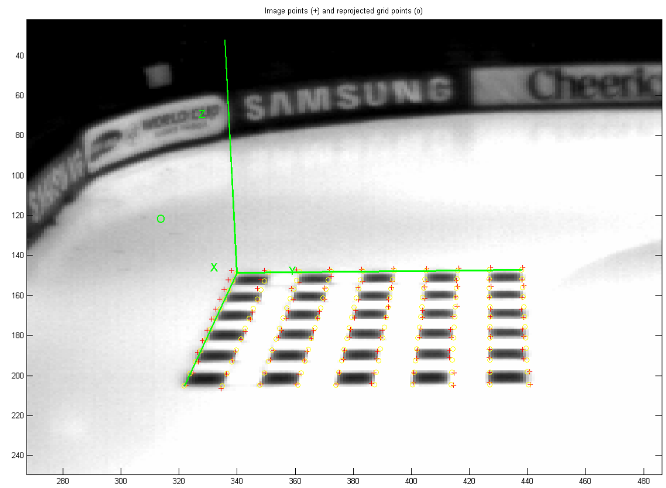

Figure 1. Result of the Zhang calibration method on a 1 meter wide checkerboard pattern used at the Pavillon de la Jeunesse, Quebec city.

Visually, this calibration method give good results, as shown in Figure 1. Nevertheless, the input samples (Figure 2) provided were too correlated spatially. The calibration pattern needs to be imaged under a variety of poses while covering most of the sensor. This is mainly because the pattern needs to be very large and the observation points scattered around the arena. This specification could not be met due to the limited physical access over the ice.

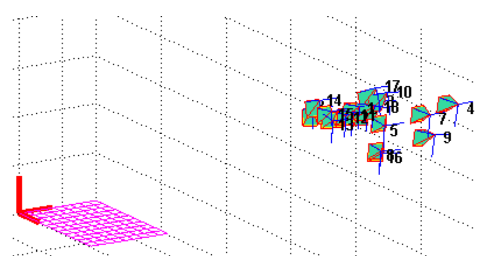

Figure 2. The image samples used as inputs to the Zhang method. The samples are closely correlated due to the environment.

A. Image rectification

On the official speed skating rink, several features are localized with precision, namely the starting and finish lines, start corridors, inner rink and turn markers. Those features are paired to the pixel coordinates of the camera frames. As shown in figure 3, image rectification warps the source image to the new referential by applying a high-order polynomial transformation.

Matlab's warpPerspective and OpenCV's imTransform implementations were tested, but Manifold GIS rectification

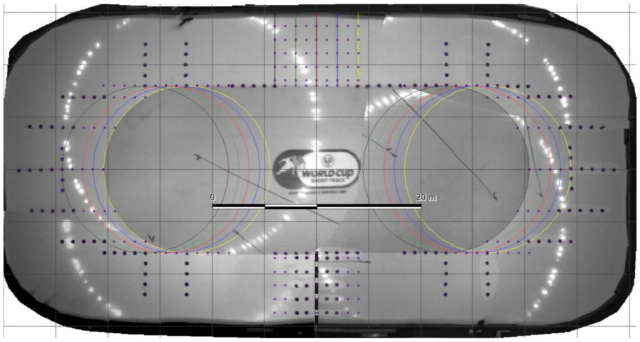

Figure 3. Result of a 3^{rd} order image rectification of the four input images over the orthographic referential in Manifold GIS.

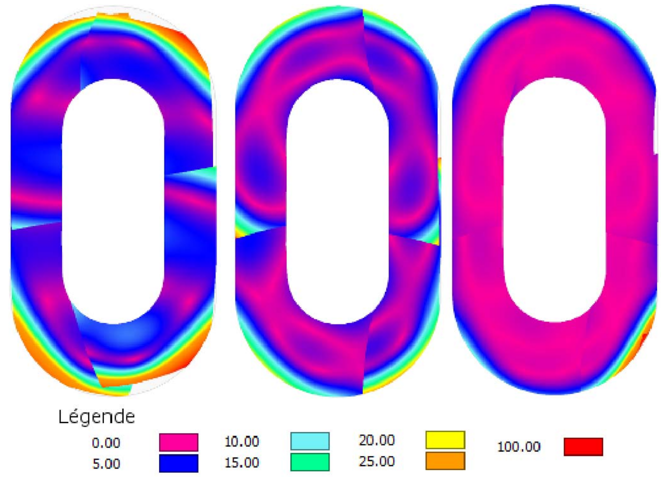

Figure 4. From left to right, map of the RMS back-projection error in pixels, for the polynomial rectification of order 2, 3 and 4 of the four input images of the skating rink.

was selected in order to lower the number of software dependencies in the system and to improve design cohesiveness. The equation system of this type of polynomial transformation is based on Equation 2.

$$x\prime = \sum_{i}^{I} \sum_{j}^{J} a_{i,j} x^i y^j \tag{2a}$$

$$y\prime = \sum_{i}^{I} \sum_{j}^{J} b_{i,j} x^i y^j \tag{2b}$$

For all pairs of points, we have to find the coefficient $a_{i,j}$ et $b_{i,j}$ linking all points to their projection ($x\prime$,$y\prime$). As it is a linear equation system, SVD factorization can be employed. The color of the resulting pixels is then determined by bilinear or bicubic interpolation.

B. Back-Projection error

The RMS back-projection error is obtained by applying the inverse transformation on a rectified image and by determining the Euclidian distance between the new pixel position and the original one. It therefore cumulates the imprecision of both the direct and inverse transformation. Figure 4 illustrates the magnitude of the errors on the ice rink.

In figure 4, we can see that RMS error grow rapidly outside the area covered by control points, even diverging near the sides. Inside the race corridors, for a 4^{th} order transformation, the RMS error is less than 1 pixel.

Table I
TABLE OF THE RMS RECTIFICATION ERROR IN PIXELS, FOR THE FOUR CAMERAS, FOR TRANSFORMATIONS OF 2^{nd}, 3^{rd} AND 4^{th} ORDER.

Order	Cam 0	Cam 1	Cam 2	Cam 3	Mean
2	7.884	6.482	5.528	6.813	6.676
3	4.394	3.436	3.545	3.201	3.644
4	2.503	1.064	1.269	1.258	1.523
Control points	95	91	95	79	90

In Table I, we note that for a 4^{th} order transformation, the mean RMS error for all four cameras is **1,523 pixels**. When excluding the outlier points outside the race corridors, the average RMS error is reduced to approximately **0,447 pixels**. Assuming that half of this error is due to the direct transformation, the mean RMS error for the race corridors is reduced to **0,2235 pixels**. By taking in account the image resolution and the time delta, the uncertainty on instant speeds due to the rectification process is $\pm 0,48$ m/s, or $\pm 1,75$ km/h.

V. OPTICAL TRACKING

Before being rectified onto the orthographic referential, trajectories of the skaters need to be extracted from the video sequences by optical tracking. Athletes are detected by a background subtraction, modeled by their color distribution and tracked by a particle filter.

A. Pre-processing

One of the most common way to estimate the foreground of a sequence is by employing a mixture of Gaussians[30] where each pixel is modeled independently. Tian [31] improves the response to shadows and varying lighting conditions. In the present research, the problem is very well constrained. A simple subtraction is carried between the current frame an empty background, obtained by averaging several frames of the input sequence.

As shown in Figure 5, the foreground probability map is binarized by Otsu's [33] thresholding method. It is first applied globally to the whole image to extract rough blobs, then it applied locally in the neighbourhood of those blobs. The resulting segmentation is less sensible to cast shadows. This leads to a better tracking initialization.

B. Particle filtering

The particle filter, also named Condensation [34] algorithm or sequential Monte Carlo approximation, is a

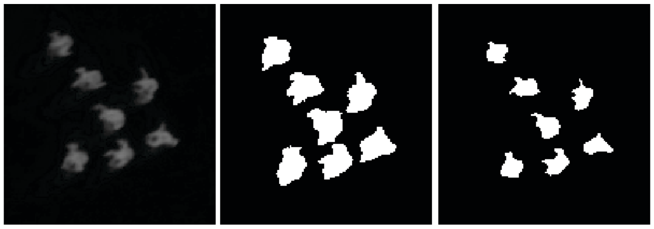

Figure 5. Foreground probability map obtained by subtraction (left), binary segmentation of the map by Otsu's thresholding method using the whole image (center) and a local region of interest (right).

common Bayesian technique often used in optical tracking applications [35], [36], [37], [9], [34].

Observations are modeled by one or several characteristics, such as shape, appearance, keypoints, texture or color[38]. In speed skating, color can help locate the head of the skater as every athlete in a competition is wearing a bright yellow cap on its helmet. In most sports, countries adopt unique color palettes on their suits. On one hand, color not very discriminant in training because most of the time, athletes are from the same country. On the other hand, the sensitivity of color cameras tend to be much lower than monochrome ones because of the presence of a Bayer filter. In order to obtain a sharp image at a relatively high framerate, the ambient lighting needs to be augmented. This is not possible in a sports arena. Therefore, color information was discarded in the overall solution.

The selected observation model is based on a simple 16-bins histogram of grey levels [9], [10], [6]. This approach is fast to compute and is robust to partial occlusions, but perform badly in complex environments. In the current application, the problem is relatively simple, the background being a uniform sheet of ice.

Each particle is moved in state-space according to its dynamic model. In order to predict the position of targets, particle filters often defines autoregressive dynamic models [37], [9], [34] where the predicted position is inferred from previous positions.

A 1^{st} order model, also known as a random walk or a Brownian motion, adds Gaussian noise $N(0, \Sigma)$ to the last known position x_{t-1}. A 3^{rd} order model predicts the position x_t by adding the displacement due to both the velocity and to the acceleration to last known position, plus noise. In the prediction phase, particles are propagated according to either a 2^{nd} and 3^{rd} order model according to probabilities P_{2nd} and P_{3rd} respectively, where $1 - P_{2nd} - P_{3rd} > 0$.

Observed short track speed skating trajectories are highly constrained to the rink. Skaters are therefore most of the time turning around a center of rotation. Instant center of rotation are extracted by a sampling three equidistant points from the trajectories and by applying a circular regression [39].

It can be seen on Figure 6 that instant centers of rotation can be used to localize strokes, where the leg extension is maximal and where the optical center of mass is the furthest from the overall trajectory.

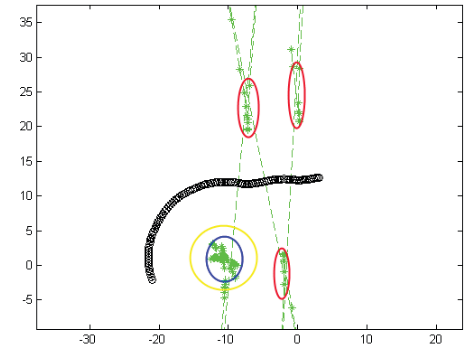

Figure 6. Clusters of instantaneous local centers of rotation (in green) indicate a turn (blue oval) and maximal extension during a stroke (red ovals) for tracked data. A priori, the center of rotation during a turn is expected to fall in the yellow oval.

To better capture the rotational motion of the skaters, velocities and accelerations can be carried out in Euclidian coordinates as well as polar coordinates. During the prediction phase, the probability P_e that a skater is in a turn is proportional to the distance of its instant center of rotation relative to the expected center of rotation for this turn. With higher values of P_e, the algorithm carries out the prediction in polar coordinates instead of Euclidian coordinates. Instant centers of rotation are also a key component in the physical model that links speed, lean angle and centripetal force in the simulator.

VI. Simulated Data

Before power can be estimated from measured data or used in the dynamic model of the tracking system, human performance analysis is carried out for generated parametric trajectories. In the current implementation, the simulation does not interact with the optical tracking yet. It is provided to Speed Skating Canada as a post-hoc analysis tool allowing the modelisation of the domain.

The Figure 7 presents an accurate geometrical model. The *straight* correspond approximately to the arc formed by the exit $D1$ of a turn and the entry $D3$ of another, while passing by the straight width $D2$. The lap generator receives five input parameters:

- the turn radius r or corresponding to the segment $V0V2$;
- the angle of entry θ formed between $V0V1$ and $V0V2$;
- the transition time t elapsed between the straight and the turn, spanning over $T0T1$;
- the total lap time T;
- the width of the straight w corresponding to segment $X0D2$.

For each point along the generated parametric lap, several physical properties are computed according to classical

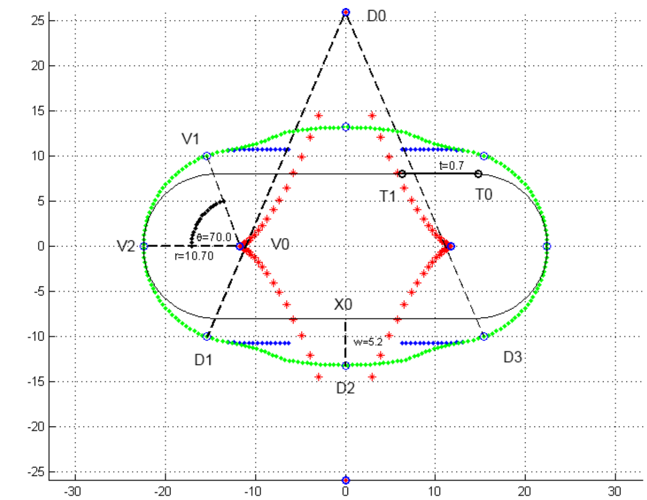

Figure 7. A non-accelerated parametric lap generated by the simulator. In green is the trajectory of the skater, and in red, its instantaneous center of rotation as determined by a circular regression [39].

mechanics, including the lean angle of the skater ϕ, the centripetal force F_{cent} and the additional mass M_{add} felt by the skater along the axis of its body.

$$P_t(t) - P_f(v) = dE/dt = M * v * a = 0 \qquad (3)$$

$$P_t(v) = F_{skate} * v + F_{air} * v \qquad (4)$$

The simulation is not accelerated. The variation of kinetic energy dE/dt is therefore zero. The simulator takes in account the friction forces F_{ice} and F_{air} to compute instant total power output P_t at every point using Equation 4. In order to compute air friction F_{air}, the aerodynamic drag coefficient $C_dA(v)$ used in the simulator was measured from wind tunnel tests carried out by CNRC on three short track speed skaters.

As a result, the average power output produced by the simulator for a typical male skater is 261,64 Watts, against 256 Watts for Van Ingen Schenau [40]. Sources of internal power loss, such as motion of the limbs, are difficult to model. The simulated power output therefore only take in account about 58% of the real power output. This scale factor is an ad hoc value found in the literature that hasn't been fully validated.

VII. Results

To assess the tracker performance, a ground truth of 1163 points, each measured two times, was acquired. A total of 15 independent trajectories of sufficient length was sampled. The position of the point correspond to the center of mass of the athlete, located approximatively between the belly button and the coccyx.

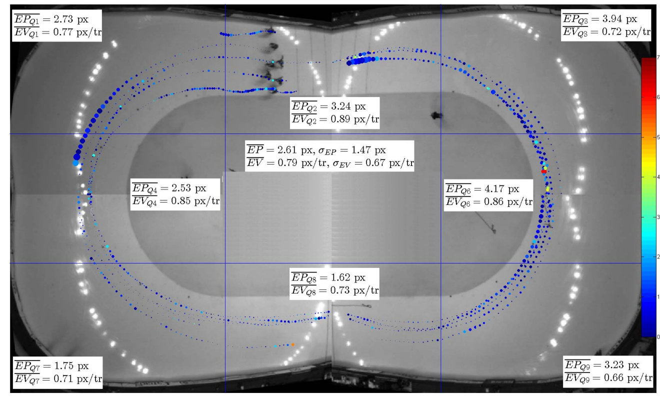

Figure 8. Errors of the optical tracker for each of the nine Q quadrants considered. The color of the points indicates error on instant velocity (EV) in pixels per frame, while the size of the points is proportional to the the square of the absolute error on position (EP) in pixels.

A mean error $EP = 2.61$ pixels was obtained for all points produced by the tracking module. This relatively large uncertainty is caused by shortcomings in the observation model. Moreover, the filter tend to drift away from this initial model at each iteration, even more when the skater's apppearance changes or when close to the maximal optical distortion zones. When taking in account the mean error on velocities $EV = 0.79$ pixels, EP seems to indicate a systematic error between the optical center of mass and the decision of an human. A human observer can use hierarchical cues to assess the position of the center of mass, such as limbs and head relative positions. The observation model simply locates the skater by computing the optical center of mass of its blob. In other words, whatever the source, the location of the center of mass is consistent from frame to frame, resulting in a small error on velocities.

The uncertainties on instant speeds due to positioning error is $\pm 1,04$ m/s or $\pm 3,76$ km/h. When added to the rectification error ER of $\pm 1,75$ km/h claimed in section IV-B, the overall uncertainty on velocities is $\pm 5,51$ km/h, or about $12,5\%$ of the cruising speeds. This error is rather large and implies that data series should be filtered before all quantitative analysis.

VIII. Discussion

The calibration procedure gave more than satisfactory results. The protocol could be improved by automation of some of the steps and by using more precise apparatus. The optical tracker exhibits significant errors that can be minimized by a more robust and modern filter, a better observation model, a higher input resolution and and a more elaborate interaction model between skaters, amongst others.

One of the main innovation of the developed model is the use of instant rotation centers. This parameter allows the computation of fictional forces which are a very important cause of exhaustion in this sport. Apart from a more accurate picture of the total power output, centers of rotation can also be used to detect and measure the amplitude of strokes. This data would prove useful in the creation of an accelerated simulator.

A complete study of short track speed skating performance requires a exhaustive modelisation of geometrical [24], biomechanical, physiological and cinematic phenomenas. Once obtained on the basis of a single lap, this unified model could be used to optimize the effort for a whole race according to the athlete's capacities and the race context.

IX. Conclusion

In this paper, we propose a novel GIS-centric computer vision system for tracking speed skaters in competition and training situations. We also propose the geometric, physical and power-based models and tools to evaluate human performance.

The main problem remain the degradation of the tracking performance when skaters are moving close to each other, causing prolonged occlusion. In the future, it is assumed that the inclusion of an accelerated power-based model in the tracker's dynamic model will improve prediction. By providing a cleaner and more complete signal, an active external positioning system would be highly recommended to help develop accurate models. Moreover, as aerodynamic drag is by far the most important factor in the power output, future models would benefit from being realized in collaboration with CNRC.

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