A System for Acquisition and Modelling of Ice-Hockey Stick Shape Deformation from Player Shot Videos

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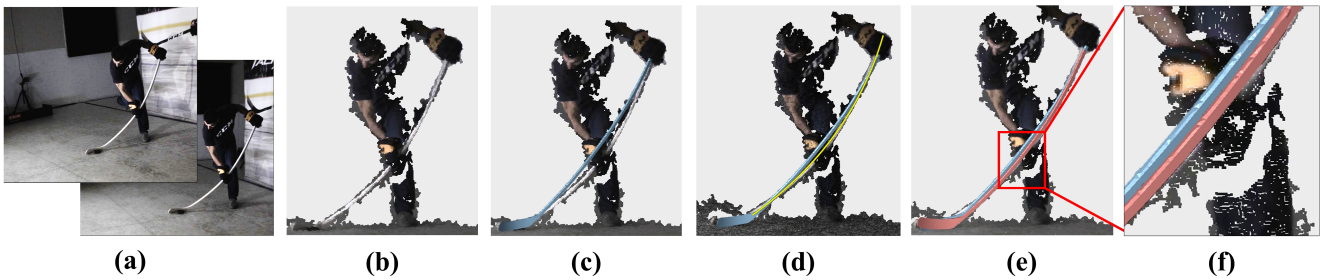

Figure 1. Our stick acquisition pipeline: a) Input images for each frame; b) Point cloud reconstruction; c) Template geometry (blue); d) Reconstructed stick bend (green); e,f) Deformed hockey stick (red).

Abstract

In Ice-Hockey, a player shot significantly deforms the hockey-stick. Since this deformation plays a dynamic role in determining the flight of the puck, it is used in the study of hockey stick shapes, material properties, match to player style, etc. Reconstructing the deformable 3D shape of the stick during the course of a player shot has important applications. In this work we present a new, low cost, portable system to acquire videos of a player shot and to automatically reconstruct the deformation in 3D shape of the stick. The point clouds obtained are low resolution and noisy, as it is difficult to separate players hand geometry from the stick. We use the medial axis to constrain the point cloud to stick only geometry, and then use physics-based co-rotational FEM to determine the stick bend. We have tested the system with different sticks, players and shot styles, and our system yields accurate reconstructions. The results are discussed both qualitatively and where possible, quantitatively.

1. Introduction

Ice-Hockey is characterized by high intensity intermittent skating, rapid changes in velocity and duration, and frequent body contact [27]. It has become increasingly sophisticated in terms of technological innovations, equipment design and improvements in training, coaching and game strategies [31, 15]. It is an equipment heavy game and one of the most distinctive pieces of equipment in the game of Ice-Hockey is the stick [17]. The global Ice-Hockey stick market was valued at 240 million USD in 2018 and will reach 320 million USD by the end of 2025, growing at a CAGR of 3.6% during 2019-2025 [2].

Hockey sticks and their shape deformations have been studied since early seventies for their dynamic role in the game of Ice-Hockey. The combination of curved blades and stick bending phenomenon enables projection of the puck with both high speed and accuracy [28]. A stick's utility as well as affordability are highly dependent on its material properties [12]. Rules of the game stipulate on the dimension of the shaft and blade; however, there is no restriction on the material composition of sticks [18]. As such, stick manufacturers have focused on making use of composite materials which allows them to modify the sticks' mechanical characteristics. This in turn helps tailor the sticks to meet the individual player specifications. In fact, research suggests that one of the primary reasons for elite players generating much faster shots is their ability to flex their hockey stick [38]. A lot of work is carried out on the investigation of sticks' performance characteristics from the Biomechanical perspective [24, 25, 21], and from the materials perspective [30, 41, 40, 4, 19, 20]. 3D reconstruction of the stick shape and its bend is at the core of a lot of research topics involving study of material properties of a hockey stick. In this work, we propose a complete framework, comprising of completely portable high-speed stereo video cameras, for acquisition and 3D reconstruction of a stick along with its deformation during various hockey shots. We have specifically focused on two widely used shots, namely, slap shot and wrist shot.

Capturing the shape of the blade during a shot is challenging because the hockey stick is a very thin object and when the acquisition cameras are positioned one side, only part of it is visible at a time. Additionally, the capture volume needs to be fairly large with the cameras positioned safely away from the player and there are occlusions. The motion is very fast therefore the setup required must capture at least 250 frames per second (fps). This implies that the images will be noisy or dark, and to achieve this frame rate with relatively inexpensive cameras requires a trade-off between spatial and temporal resolution, which in turn significantly impacts reconstruction accuracy. In our setup in order to accomplish 250 fps, we chose a spatial resolution of 672×608.

Compared to work reported in the literature, the primary new contributions of this work are as follows:

1. A new, low cost, portable system covering the entire pipeline from player-shot video capture to 3D reconstruction of the deformable hockey stick,
2. Frame by frame construction of the changing 3D shape of the hockey stick during the course of a player shot
3. An innovative method using the medial axis to eliminate extraneous points from noisy point data and accurately recover the 3D point cloud of the hockey stick.

The rest of this article is organized as follows; Section 2 discusses related work. Section 3 provides an overview of the proposed system. The acquisition pipeline and the stick shape deformation process have been detailed in Section 4. Results are presented with relevant discussion in Section 5 and finally, Section 6 concludes the paper with limitations of the proposed work along with some planned future work.

2. Related Work

Various research studies on the game of Ice-Hockey are available in the literature looking at different aspects of the game. A recent study in pose estimation and action recognition in the game of Ice-Hockey is presented by [10]. For the purposes of stick performance analysis, however, 3D reconstruction/representation of the hockey stick is imperative, and not much work has been reported on this problem.

Optical motion capture studies from the perspective of 3D representation are available in the literature for analyzing various shots employed in the game of Ice-Hockey. Some of these studies have been carried out in a simulated environment i.e., by making use of the synthetic ice [14, 26, 13, 20]. A recent study has also been carried out on real ice with professional hockey players [36] to study the 3D kinematics of various shots played in Ice-Hockey. A few of the major drawbacks in using these high-end, high accuracy motion capture equipment are (i) the intrusive nature of the markers, (ii) high cost of equipment and its set-up, and more importantly (iii) non-portable setup. 3D reconstruction from images and video has been at the core of many of the research problems for several decades. A lot of literature is available in both computer vision and computer graphics domains for 3D reconstruction, and similar representations often appear in both the domains. This is owing to the fact that vision researchers are solving the shape recovery of real objects problem, whereas graphics researchers are simulating the deformations of virtual ones [34]. The approaches can be broadly classified into structure from motion (SFM) and template based reconstruction or shape from template (SFT) [43].

In SFM approaches, a set of points are tracked on a set of images, which then are used to reconstruct the objects. A study on recovering the shape and motion of a single rigid object is presented by [37]. An assumption of object shape being a linear combination of some basis shapes has been made to recover shapes of deformable objects in [9, 8]. Stick movement in Ice-Hockey is very fast and such rapid motion leads to large frame-to-frame differences, which makes tracking challenging, especially for highly deformable objects [22]

In SFT or template-based reconstruction approaches, a shape template of the non-rigid object is available a priori. This template is then deformed using motion priors or physics-based principles to match the current observation. This has been demonstrated to estimate the shapes of human faces by [7]. SFT approaches can be further subclassified based on input data, namely monocular, RGB-D and stereo image sequences.

Monocular Data: Wangg et al [39] have proposed a method for reconstructing 3D face expressions from monocular video sequences using a 3D face template mesh. Parashar et al [29] have proposed volumetric SFT to reconstruct an object's surface and interior deformation using a single image and a 3D object template. Perriollat et al [32] have proposed reconstruction of sheet-like inextensible surfaces using a single image taken from a camera with known intrinsic parameters and a template. Alldieck et al [3] have proposed a method to create personalized realistic 3D human models from a monocular video sequence and a parametric SMPL body model. Zuffi et al [45] have proposed a method to obtain 3D textured animal model, given a set of images of the animal annotated with landmarks and silhouettes. Deep learning has also been employed in several research works for 3D object reconstruction based on a single image. A detailed review on state-of-the-art deep learning methods for image-based 3D object reconstruction is also available in the literature [16]. The difficulty in using this monocular approach for our problem is that during a shot, the orientation of the hockey stick keeps changing very rapidly and a single view is unable to provide all the information needed for deformation modeling.

RGB-D Data: Microsoft introduced Kinect in 2010 and ever since affordable RGB-D devices like Intel RealSense, Primesense Carmine, Google Tango, Occipital have made RGB-D database creation very easy. Many foundational research problems have been revisited and rethought to

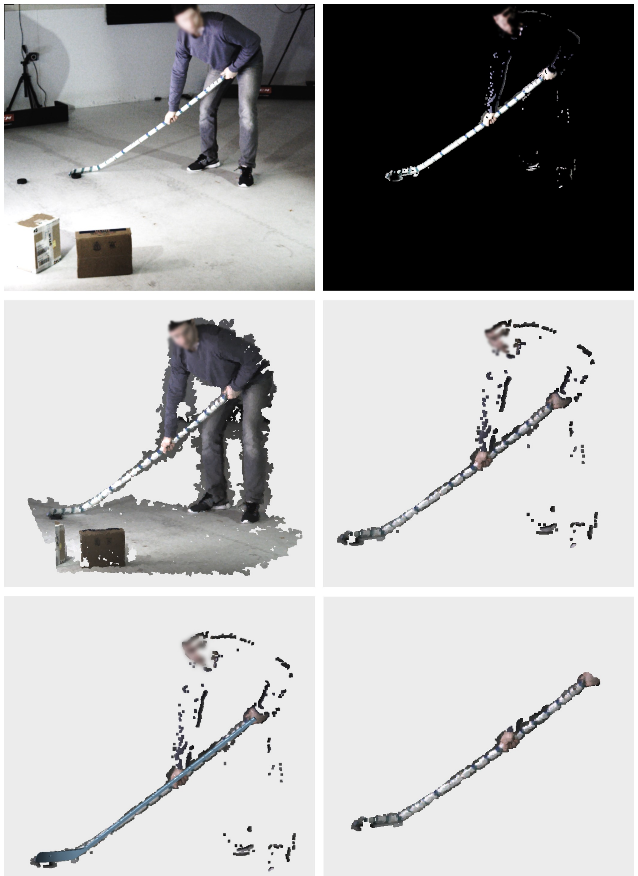

Figure 2. Vertex pruning process. top-left) Input image; top-right) Masking out static pixels; mid-left) Initial point cloud; mid-right) Pruned point cloud based on the pixel mask; bottom-left) Initial point cloud with the aligned template; bottom-right) Pruned point cloud based on the proximity to the aligned template.

make best use of the new capabilities of RGB-D cameras, and a detailed survey is available in [44]. Li et al [23] have proposed a method to reconstruct the 3D human body model from a single RGB-D image and a parametric body model. Tao Yu et al [42] have proposed a new real-time system that combines volumetric dynamic reconstruction with data driven template fitting to simultaneously reconstruct detailed geometry, non-rigid motion and the inner human body shape from a single depth camera. Raoul de Charette et. al. [11] have proposed a method to reconstruct arbitrary 3D revolving objects (in context of live pottery making) that handles deformation as well as occlusion using one or more depth sensors. The primary problem with these acquisition systems is that the speed of capture is very low and a fast-moving hockey stick is difficult to capture using current state-of-the-art RGB-D sensors. Therefore, we opted for a stereo setup consisting of two high-speed global shutter cameras with hardware temporal synchronization.

3. System Overview

We designed and built a complete system (software pipeline and hardware setup) that can acquire the geometry of a hockey stick during the execution of a shot, including the stick bending. We employ a stereo setup consisting of two spatially and temporally synchronized cameras that acquires 275 fps. Each pair of images (Fig. 1 a)) is processed through our software pipeline obtaining one triangular mesh for each frame (Fig. 1 f). As we are using an initial 3D template of the hockey stick, all triangular meshes are compatible (i.e. they have the same set of vertices and the same set of triangles). This is important for the subsequent analysis of the shot and stick deformation.

Using stereo reconstruction, we first obtain a point cloud per frame. However, this point cloud contains the stick and all the surrounding environment: the player, the rink, etc. depending on the setup. Using the temporal information from the next frame, we prune the points that are static from frame to frame.(Fig. 2 right-middle).

The next step is to rigidly fit the template to the point cloud. As the stick undergoes a lot of deformation we cannot use the geometry of the straight stick as a template in all frames, therefore we use the reconstruction of the previous frame as the template for the current frame and we use the Iterative Closest Point (ICP) [5] algorithm to rigidly align the template. After this rigid alignment, we perform a secondary pruning of the point cloud using the distance to the aligned stick template as a criterion (Fig. 2 right-bottom). This is necessary because the pruning based solely on motion may still contain points belonging to some parts of the player body that are in motion (Fig. 2 right-middle).

We further need to deform the template stick to match the reconstructed point cloud. This deformation operation has two ingredients: a deformation model that can be applied to the stick geometry and a constraint mechanism that ensures the deformed template matches the point cloud.

For the physics-based deformation model, we use the co-rotational Finite Element Model (FEM) method similar to [6]. While there is a rich set of deformation models, a FEM model was the most appropriate because we are aiming for a physically correct deformation. The co-rotational FEM model is accurate, efficient and numerically stable, particularly suited for deformation that is primarily rotational as it is in the case of the hockey stick.

The second part is to apply constraints to the hockey stick in order to deform it to fit the point cloud. However, the point cloud is very noisy due to (i) relative low resolution of the cameras, (ii) large distance from the subject and (iii) thin geometry of the hockey stick. Furthermore, the stick is partially occluded by the hands or gloves of the player. Therefore, using the point cloud directly results in artifacts as illustrated in Fig. 3. To stabilize the geometry we robustly fit a quadratic curve to the medial axis of the

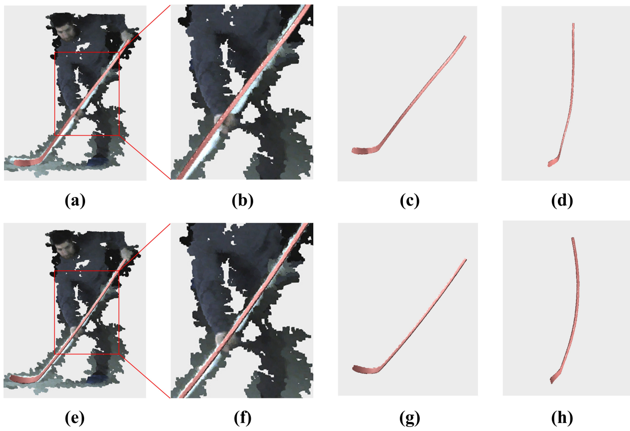

Figure 3. Comparison between fitting the point cloud directly or using the medial axis on a given frame. a-d) Result fitting the point cloud directly. e-h) Result using the medial axis. The results when using the point cloud directly exhibit clear undesirable artifacts while the result using the medial axis conforms well to the real stick shape.

geometry of the hockey stick and we use this curve to apply constraints to the hockey stick as illustrated in Fig. 4. The next section provides more details of our acquisition system and deformation process.

4. Acquisition Pipeline

4.1. Hardware Setup

Since additional goals of our system are portability and low cost, we selected 2 Grasshopper3 USB3 color cameras from Flir. They are vision cameras with global-shutter and temporal synchronization support. We built our own custom-made temporal synchronization box.

As the hockey shots involve high-speed motion, we needed as high as possible temporal acquisition. We could successfully acquire at 275 fps, but at the expense of reducing the resolution to 672×608 pixels. The nonstandard resolution was obtained by selecting the maximum resolution that allows for 275 fps. Experimentally, for a high-speed hockey shot, a temporal resolution of 250 was considered sufficient. However, we chose to select 275 fps as a target because a high performance athlete might shoot at slightly higher speeds than our subjects.

4.2. Point Cloud Reconstruction and Initial Pruning

We use a commercial multi-view reconstruction package: Metashape by Agisoft [1], to calibrate the setup and to get the starting point cloud per frame. As every point comes from a two image-paired pixels, we compute optical flow in the scene and we prune the points that project onto static pixels (Fig. 2).

This motion-based pruning still leaves some points located on the player body and so, down the pipeline a second pruning step is necessary. However, this initial pruning is critical, particularly in the first frame where the location of the stick in the scene is not known a priori and has to be searched. Fortunately, this pruning facilitates an efficient automatic method of positioning the stick in the scene. Furthermore, this pruning also makes the subsequent steps more efficient and with lower memory footprint as a large amount of unnecessary points is removed.

4.3. Template Deformation

To obtain the final 3D reconstructed result in every frame, we use as a template the deformed stick from the previous frame. We first align it rigidly using ICP and we perform a secondary pruning based on the distance to the template model. The resulting point cloud is very noisy and still contains some points where the hands or the glove of the player touch the stick. These are impossible to remove unless we rely on the color information, which would limit greatly the generality of the system.

To explain our deformation model we need to understand the structure of a hockey stick. A hockey stick has two main parts: the blade (the lower part used to shoot the puck) and the shaft (the longer part held by the player). Our system focuses on deforming the shaft where most of the stick deformation happens. We make the observation that the bend in the stick is relatively low dimensional and can be well approximated by a quadratic curve. Therefore, we compute the medial axis of the point cloud as shown in Fig. 4 and we robustly fit a 3D quadratic curve to the shaft.

However, this medial axis contains some outliers, and the rest of the points either belong to the medial axis of the blade or to the medial axis of the shaft. It is important to fit the quadratic curve only to the shaft, otherwise a quadratic curve is not enough to approximate the deformation of the entire stick. To accomplish this we use a RANSAC strategy: we randomly select 6 medial axis points, we compute a best fit quadratic curve. We repeat this $30,000$ times and we select the curve with the largest number of inliers. Fig. 4 shows the medial axis and the quadratic curve.

Next we need to use this quadratic curve to control the deformation process. As a deformation model, we use a co-rotational FEM model similar to [6]. In order to use this model, we need first a tetrahedralization of the template mesh. We use TetGen [35] to compute a tetrahedralization without adding new vertices. Our models have between 6100 and 7100 tetrahedra. This is a good compromise between accuracy and efficiency.

As the quadratic curve approximates the medial axis of the shaft, the constraints on the tetrahedral mesh should be done also based on its medial axis. However, if we add more vertices, associated tetrahedra will increase signifi-

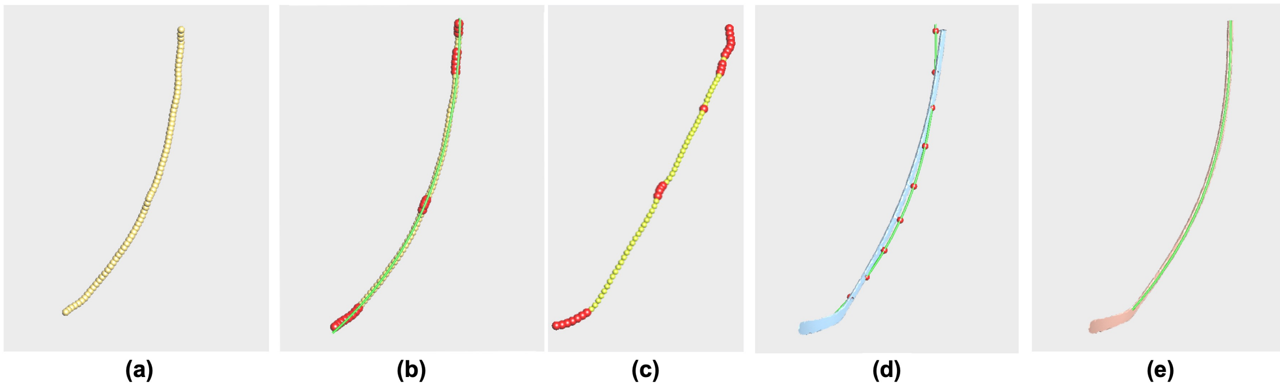

Figure 4. Quadratic fit and bending constraints: a) Medial axis of the stick geometry; b) Robust quadratic fit curve (green), inliers (yellow) and outliers (red) of the RANSAC procedure; c) Inliers/outliers from a different view; d) Quadratic curve (green) and the stick template constraints (red); e) Final result (red) overlapped with the quadratic fit

cantly the number of elements leading to numerical problems. Instead, we select the constraint points on a side of the stick as shown in Fig. 4, noting that, on the shaft, this line is parallel to the medial axis and, thus, it will lead to the same deformation, albeit translated slightly. We correct the translation by rigidly aligning the deformed model to the point cloud one last time using the same procedure as before. An additional challenge is that these medial axis constraints allow for a rotational degree of freedom around the medial axis. So, we add constraints on the blade with lower weights to correct for that.

4.4. Stick Template

In our experiments we obtained the geometry of the hockey stick by using a commercial 3D scanner or it was provided as a CAD file by the stick manufacturer. In both scenarios, we remeshed uniformly these models to around 2200 vertices to obtain our template. This approximate mesh size was chosen experimentally to balance the quality of the mesh with efficiency of processing.

4.5. Stick Alignment in the First Frame

In every frame except the first, we use the reconstruction from the previous frame as a starting point. However, in the first frame we don't have a previous reconstruction so we determine the stick pose by aligning the template to the stick point cloud. In order to do this initial alignment, we employ a feature matching approach. We used fast point feature histograms [33] (FPFH) computed on both the template mesh and the pruned point-cloud and we compute an alignment between the two shapes using a RANSAC strategy. We use 4 features to seed the alignment and we perform $40,000$ iterations.

5. Results and Discussion

We have tested our pipeline with different sticks, subjects and shot styles. In the results section as well as the accompanying video we show 4 shots with 2 different sticks, 2 different shot types and 2 different subjects.

We provide a qualitative evaluation of our method by overlapping the resulting mesh to the reconstructed point cloud as shown in (Figs. 5, 6). As can be seen by visual inspection the 3D model of the shaft matches closely the point cloud. Even subtle deformation such as the back-bend due to the moment of inertia is captured in the slap shots Fig. 5(right).

In the industry, the current state of the art in quantifying the bending of the stick is attaching markers to the hockey stick and using a state of the art motion capture (MOCAP) system to determine various characteristics of the stick such as maximum bending angle during a shot. Although the MOCAP systems are very mature and accurate, they do not capture the entire stick, only the trajectories of a few points. Furthermore, since our cameras are color cameras and the MOCAP system's cameras are infrared cameras, it is very difficult to align spatially the coordinate frame of the MOCAP system with very high accuracy. Lastly, it is very challenging to temporally synchronize the MOCAP system's data stream and our data stream. However, the maximum bend of a stick, an important benchmark for the stick deformation is independent of spatial and temporal alignment so we decided to focus on this for our quantitative evaluation.

We follow the standard industry method used to estimate the maximum bending angle. As shown in Fig. 7a,b) we attached a number of markers on the shaft in a pattern that creates three local coordinate frames $(A-C)$. Two axes are formed from the markers and the third one can be obtained using a cross product operator; the frame is then normal-

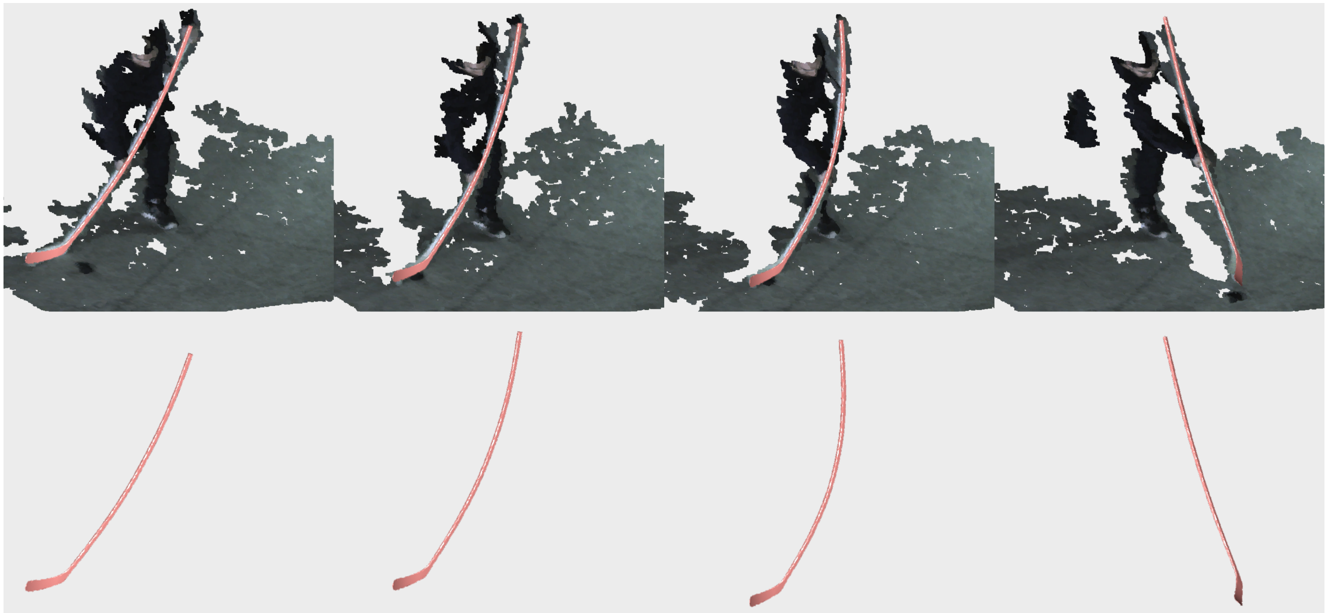

Figure 5. A few frames of a slapshot. Note the bend backward of the stick in the last frame due to the stick oscillations in the high energy shot. The entire sequence can be seen in the accompanying video.

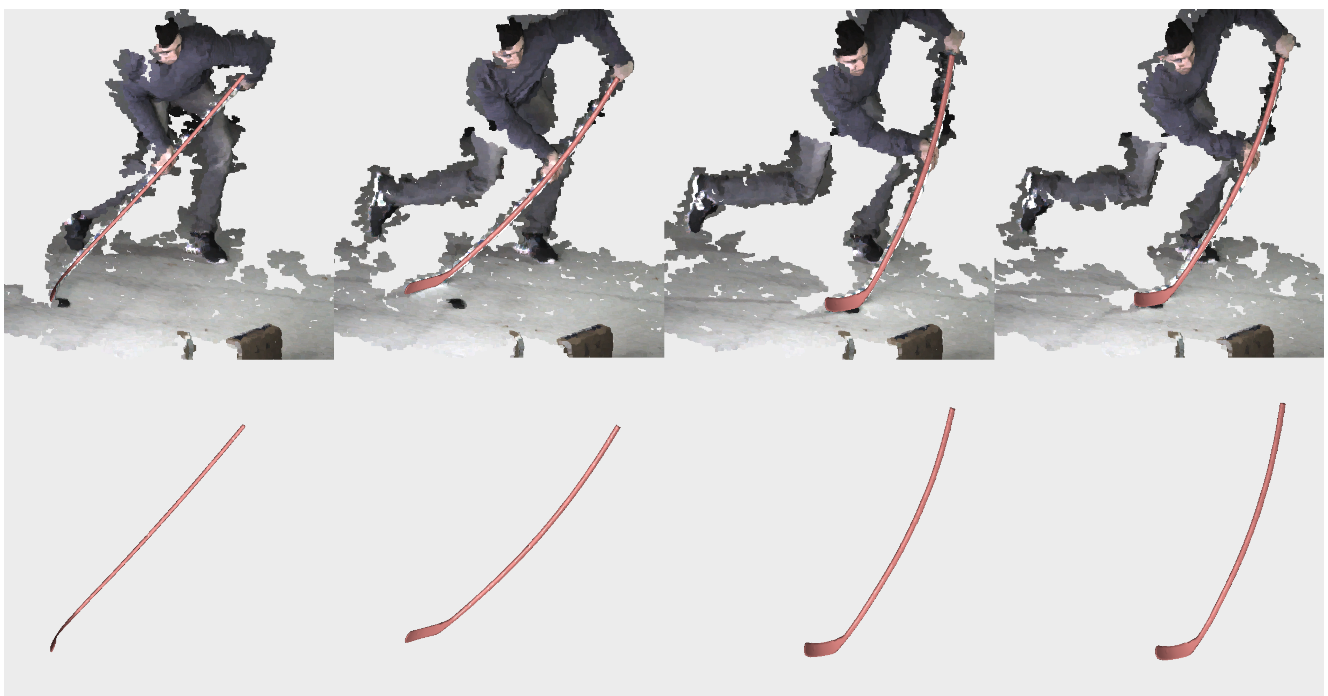

Figure 6. A few frames of a wrist-shot. Our system captures the correct orientation of the stick in both deform and undeformed configurations. The entire sequence can be seen in the accompanying video.

ized to obtain an orthonormal matrix. We computed two angles: angle 1 between the coordinate frames A and B and angle 2 between coordinate frames A and C. We mimicked the same setup on the virtual stick as shown in Fig. 7c) by manually positioning marker points. Since the the MOCAP markers are physically outside the stick, this is a source of errors. Nevertheless, we averaged the two maximum angles for 2 slapshots and 2 wrist-shots using both systems. The

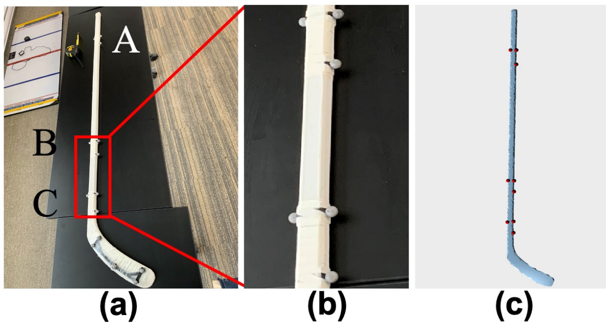

Figure 7. Comparison setup: (a), (b) hockey stick with retro-reflective markers captured by the MOCAP system. (c) Our template with our virtual markers (red).

	Slap Shot	Wrist Shot
Max Angle MOCAP 1	21.8	20.0
Max Angle Our System 1	23.65	22.05
Diff 1	1.85	2.05
Max Angle MOCAP 2	26.2	23.15
Max Angle Our System 2	28.35	26.65
Diff 2	2.15	3.5

Table 1. Quantitative comparison of the maximum bending angle with a MOCAP system

results are presented in Table 1. The expected difference in the maximum bending angle is about 4 degrees. It is important to note that some of this error arises due to somewhat imperfect alignment of real and virtual markers.

The running time is dominated by the bending step that takes on average 87 seconds per frame. All the rest of the steps combined take 15 seconds per frame for a total combined time of about 100 seconds per frame. The computer that we used to drive the acquisition has an Intel(R) Core(TM) i7-6700 CPU running at 3.40GHz with 16 Gb of RAM.

6. Conclusions, Limitations and Future Work

In this work we presented a complete hardware setup and software pipeline for 3D acquisition of a hockey stick during a high-speed hockey shot. The hardware setup is portable and relatively inexpensive. Aside of a few small initialization per-sequence parameters that can be set within a few minutes, the processing is completely automatic. Our method uses a template, which enables the same model to be used in all frames. This allows for a rich analysis of the shot such as bending angles, key-point trajectory and tensor analysis of the tetrahedralization of the 3D mesh. We have tested our pipeline with different sticks, subjects and shot styles and in all cases the reconstructed results match well the point cloud.

One of the main limitations of our work is that it does not deform the blade of the stick (i.e., the bottom part that touches the puck). This is because there is a lot of ambiguity in the reconstructed geometry because of the proximity of the blade, puck and floor. We will address this issue by detecting and removing the flat floor and detecting and separating the puck in the scene.

Another limitation is an over reliance on the initial reconstructed point cloud that is very noisy. In the future work, we are planning to replace the stereo reconstruction with a visual hull reconstruction using image-based stick detection in each image.

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