EXPLOITING HUMAN BIPEDAL MOTION CONSTRAINTS FOR 3D POSE RECOVERY FROM A SINGLE UNCALIBRATED CAMERA

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Abstract: A new method is proposed for recovering 3D human poses in video sequences taken from a single uncalibrated camera. This is achieved by exploiting two important constraints observed from human bipedal motion: coplanarity of body key points during the mid-stance position and the presence of a foot on the ground – i.e. static foot - during most activities. Assuming 2D joint locations have been extracted from a video sequence, the algorithm is able to perform camera auto-calibration on specific frames when the human body adopts particular postures. Then, a simplified pin-hole camera model is used to perform 3D pose reconstruction on the calibrated frames. Finally, the static foot constraint which is found in most human bipedal motions is applied to infer body postures for non-calibrated frames. We compared our method with (1) "orthographic reconstruction" method and (2) reconstruction using manually calibrated data. The results validate the assumptions made for the simplified pin-hole camera model and reconstruction results reveal a significant improvement over the orthographic reconstruction method.

1 INTRODUCTION

Recovery of 3D posture sequences provides essential information for the analysis of human behaviour and activity. Although computer vision systems have been proposed, they either rely on controlled environments involving several cameras or are limited to specific human activities. Therefore, they cannot be used in most real-life applications, such as the detection of antisocial behaviours from images captured from a CCTV camera, where only data recorded by a single uncalibrated camera are available. Consequently, human pose recovery from a single uncalibrated camera is still one of the major challenges facing the computer vision community.

The goal of pose recovery is to localise a person's joints and limbs in either an image plan (2D recovery) or a world space (3D recovery), which usually results in the reconstruction of a human skeleton. In this work, we concentrate on 3D pose recovery. The success of pose recovery is measured in terms of posture error，i.e. the average Euclidean distance between corresponding joints of the recovered and actual postures by aligning two bodies with optimal scaling, translation, and rotation. This metric reflects the real dissimilarity between two postures.

In this paper, we propose a novel method for estimating a 3D pose from 2D joint locations using a single uncalibrated camera. Assuming 2D positions of these key points have been extracted from a video sequence, we are able to perform camera auto-calibration for some key frames automatically selected in the sequence (Kuo et al., 2007). This exploits a human bipedal motion constraint that certain body joints become coplanar within a motion cycle. This provides sufficient knowledge for reconstruction of a 3D figure in a world space using a pin-hole camera model. In order to recover poses for other frames, another human bipedal motion constraint, i.e. the presence of a foot on the ground – i.e. static foot - during most activities, is exploited to propagate 3D posture reconstruction from one frame to the next.

The structure of this paper is organised as follows. After presenting relevant literature review, we detail in Section 2 our pose recovery algorithm. Then, experiments to validate our method with quantitative results are given in Section 3. Finally, conclusions and future work are addressed in Section 4.

1.1 Related Work

Since geometric camera calibration reveals the relationship between the 3D space that is viewed by the camera and its projection on the image plane, it is a key for the reconstruction of a 3D articulated structure. The common practice for calibrating cameras is to obtain point correspondences between a known calibration pattern and its projection on the image (Tsai, 1987). Although such process is straightforward, it is very often unpractical as cameras often change position, their number may be very large or physical access to them is impossible. In order to deal with this issue, Taylor offered a pose recovery method which does not require any camera calibration (Taylor, 2000). He exploits an orthographic projection model that assumes 3D objects are very far away from the camera thus the depth of their surface points are almost constant. Although it has been widely used (Mori and Malki, 2002, Mori and Malki, 2006, Remondino and Roditakis, 2003), as we shall see in our result section, accuracy is compromised by such a strong assumption. Inspired by Taylor's work (Taylor, 2000), our method does not required any manual camera calibration and relies on the location of 2D image key points, i.e. joints, as an input. However, it uses bipedal motion constraints to recover more accurately 3D poses.

The extraction of 2D joint positions from an image has been a very active field of research (Ren et al., 2005, Kuo et al., 2008, Balan and Black, 2006, Urtasun et al., 2006). Ren et al. extracts body segments by exploiting parallelism and pairwise constraints of the body parts (Ren et al., 2005). Kuo et al. extended this approach by adding other image cues, i.e. colour and motion, which are informative regarding body part location (Kuo et al., 2008). Others use a Wandering-Stable-Lost framework to track 2D body parts/key points through the sequences (Balan and Black, 2006, Urtasun et al., 2006).

Most pose reconstruction methods rely either on multiple cameras (Bhatia et al., 2004, Izo and Grimson, 2007), and/or assume specific types of activities (Bhatia et al. 2004, Elgammal and Lee, 2006, Tian et al., 2004, Lim et al., 2006, Ek et al., 2008). Moreover, some of them require manual initialisation of their 3D tracker (Balan and Black, 2006, Urtasun et al., 2006, Martinez-del-Rincon et al., 2008). Therefore, all these constraints dramatically limit the practical applications of those systems.

Our approach exploits general constraints imposed by human bipedal motion. They include the presence of at least one foot on the ground during most activities; this constraint has already been used successfully in 2D body tracking (Martinez-del-Rincon et al., 2008). These bipedal constraints are much less restricting than assuming a specific type of motions (e.g., walking). In this work, we use such constraints for camera self-calibration from observing human motion to derive 3D poses for key frames (Kuo et al., 2007) and further infer 3D poses between key frames.

2 METHODOLOGY

2.1 3D Human Pose Recovery

Our goal is to recover 3D human postures in video sequences by exploiting human bipedal motion constraints. We propose a 3D pose estimator which generates possible 3D poses from 2D joint positions in the input image sequence. Then the most proper pose is selected by taking into account learned human motion models. Figure 1 illustrates the flow of our 3D human pose recovery. It requires an image processing task of detection of "image key points" related to postures i.e., 2D body joints, from the video. The 3D pose estimator, which is based on pin-hole projection, then transforms 2D images points to a set of 3D poses in real world, using the constraints of human bipedal motion. Based on the motion models which are learnt from dynamics and further constraints of human motion, the most likely pose can be selected among the proposed 3D poses.

Because the task of obtaining key body points from the image has been tackled in our previous paper (Kuo et al., 2008) and a paper dealing with pose selection is in preparation, in this work, we will concentrate on the 3D pose estimator which covers the pose reconstruction by exploiting human bipedal motion constraints.

2.2 3D Pose Estimator

The 3D pose estimator generates a set of 3D pose proposals from 2D joint positions based on the pin-hole projection model. First, postures are estimated automatically for a set of key frames where camera auto-calibration can be performed. Then, the other postures are recovered by propagating the parameters of the pin-hole projection model obtained for the key frames to other frames by introducing a constraint of bipedal motion.
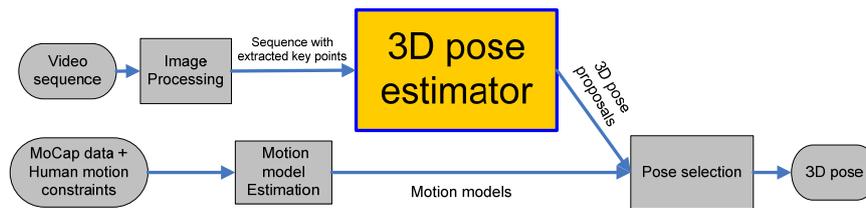
Figure 1: 3D pose recovery pipeline.

The key frames are specific frames when the human body adopts particular postures where five points are coplanar. Using those points a coplanar calibration model can be used to estimate the camera parameters (Tsai, 1987).

Figure 2 shows an in-depth insight of the 3D pose estimator. Firstly the sequence with extracted key body points is used to perform "camera auto-calibration" (see Section 2.2.1). This is an iterative process to select the key frames and to estimate calibration parameters, i.e. focal length and camera relative position. This also generates a 3D coplanar model representing the 3D configuration of the set of coplanar body joints at key frames (Figure 3).

Secondly, the pin-hole projection model is employed to reconstruct 3D postures for the calibrated key frames. The projection line of each key body point on the image can be established using the estimated focal length. Their corresponding 3D points can be located on the projection lines according to the camera relative position and the body model. The body model is a 3D skeletal representation of a human body (see Figure 3) which consists of 15 joints: shoulders, hips, shoulder centre, hip centre, elbows, hands, knees, feet and a head. It is constructed from the calibrated 3D coplanar model with known body ratios. Since this problem is ill-constrained ($\Re^2 \rightarrow \Re^3$), multiple postures are generated. A pose selection mechanism is then required to extract the correct posture. The pin-hole based reconstruction will be detailed in Section 2.2.2.

Finally, to recover postures for non-key frames, the bipedal constraint of the static foot is used. Human biomechanics reveals that at any moment at least one foot is in contact with the ground in most types of bipedal motion. This static foot exists because the body requires at least one limb to support its weight. Motion is achieved by switching weight support to the other foot. Both feet can only be off ground for a short moment if any, e.g. running. This static foot constraint can be exploited for pose recovery, since knowledge of the 3D posture at one frame also provides the 3D coordinates of one foot in the next frame. Therefore, postures can be propagated from the reconstructed

key frames to their neighbouring frames. The detail of this posture propagation using a static foot will be discussed in Section 2.2.3.
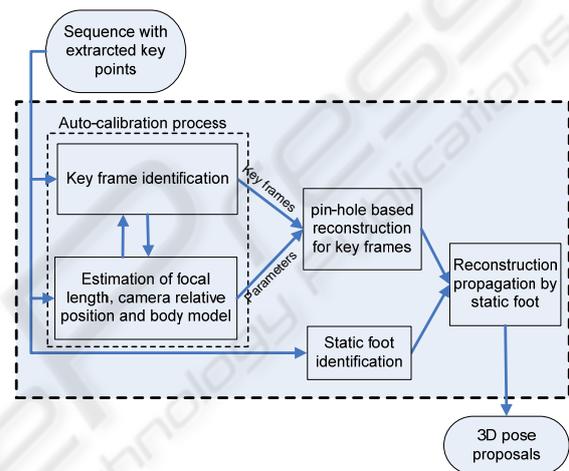
Figure 2: Details of 3D pose estimator.
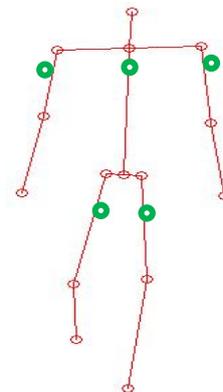
Figure 3: Body model (red) and key points of the coplanar model (green circles).

2.2.1 Camera Auto-Calibration

In order to perform 3D pose reconstruction based on pin-hole projection, it is necessary to estimate the camera calibration parameters. In order to make this task automatic, the camera model needs to be simplified. We assume the principal axis goes

through the centre of the image and there is neither lens distortion nor skew. The validity of these assumptions will be accessed in our result section.

The required projection parameters are the focal length and the camera relative position to the body. They are estimated by using the camera auto-calibration method proposed in (Kuo et al., 2007). This can summarised as follows. It is based on Tsai's coplanar calibration method (Tsai, 1987) where a set of 3D coplanar points and their projected locations on the image plane are required. A study of human biomechanics reveals that the shoulders and hips are expected to be coplanar at some time during a cycle of bipedal motion, i.e. mid-stance position. As a result, key points on (but not limited to) the shoulders and hips are suitable for coplanar calibration. Therefore, the automatic identification of the coplanar instances and the 3D structure of the key points can achieve camera auto-calibration. The core of this auto-calibration method lies on the observation that a smaller variation of the focal length estimates indicates the smaller error in coplanarity of the key points and the 3D coplanar model, which results in more accurate calibration. Tsai's coplanar calibration estimates the focal length by solving an over-determined linear system, which yields 10 estimates of the focal length. The variation of these 10 estimates is used in (Kuo et al., 2007) to reflect errors in coplanarity and 3D representation of the key points. Therefore, the key frames and the coplanar model (which is part of the body model) can be selected by minimising standard deviation of the focal length estimates through frames of the sequence and coplanar model space. Apart from the key frames and a coplanar model being identified, focal length and the camera relative position to the body in terms of rotation and translation parameters are also estimated from this auto-calibration process. Since the coplanar model has been identified, a body model is built using the shoulder length, hip length and spine length which are extracted from the coplanar model to estimate the size of the limbs (lower/upper arms/legs) and the head (Figure 3).

2.2.2 3D Human Body Reconstruction using Pin-Hole Projection Model

The pin-hole projection model, as illustrated in Figure 4, is employed for 3D pose reconstruction. This method relies on the determination of the projection line of each image point. Then, along the projection line the corresponding 3D point needs to be localised using the known distances between its neighbouring points as a constraint. This can be

achieved using the parameters estimated from auto-calibration, i.e., focal length, camera relative position and the body model. Since the 3D positions of shoulder and hip points were already estimated in the calibration process – they form the required 3D coplanar model - (see Section 2.2.1), only limbs (upper/lower arms/legs) and the head need to be reconstructed. Their positions are calculated piece-wisely from the points of the coplanar model (i.e., shoulders or hips) towards the limbs' distal ends, by applying Equation (1).

$$\|P_t - P_{t-1}\| - L_{t,(t-1)} = 0 \qquad (1)$$

$$D_t^2 - 2 D_t D_{t-1} \cos\theta + (D_{t-1}^2 - L_{t,(t-1)}^2) = 0 \qquad (2)$$

Where P_{t-1} is a 3D body key point (e.g., the left shoulder, P_{l_shdr}, see Figure 4) whose coordinates are already known, and P_t is the point which is to be reconstructed (e.g., the left elbow, P_{l_elb}, see Figure 4). $L_{t,(t-1)}$ is the expected segment length between two successive key points.

P_t and P_{t-1}'s projection lines can be established by connecting the optical centre, O, and their corresponding image points, p_t and p_{t-1}. Since P_t is constrained on its projection line, its location can be computed by using Equation (2) which considers the trigonometry of the triangle $\triangle O$- P_{t-1}-P_t. D_t and D_{t-1} denotes the distance of P_t to O and P_{t-1} to O; θ is the angle between these two projection lines (see Figure 4). Since D_{t-1}, θ and $L_{t,(t-1)}$ are known, D_t can be solved to locate P_t. As the problem is ill-constrained ($\mathfrak{R}^2 \rightarrow \mathfrak{R}^3$), the quadric formulation of Equation (2) gives us two P_t locations. This is because it cannot distinguish, from a 2D image point, whether the corresponding 3D point is closer or further away from the camera than its neighbouring point, unless some depth information is provided. As a consequence, a number of 2^{10} poses will be generated (5 coplanar points have been located uniquely by the calibration). The pose selection (see Figure 1) will then determine the most proper 3D posture for this frame among these pose proposals. To evaluate our reconstruction, in this paper, we assume pose selection is a solved problem.

2.2.3 Reconstruction Propagation using Static Foot Points

The propagation of 3D reconstruction relies on the static foot constraint which is observed in most bipedal motions where generally at least one foot stays on the ground to support body weight. Identification of static foot locations in a sequence is the key to propagate the estimated postures from the key frames to non-key frames. The 3D coordinates
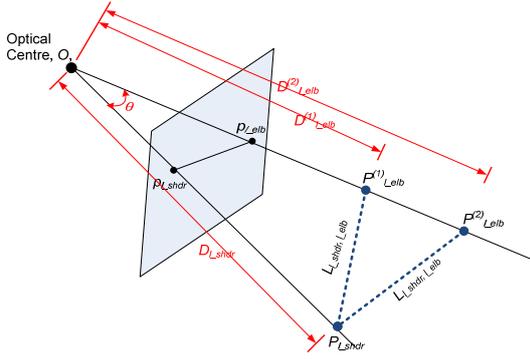
Figure 4: Pin-hole projection model for 3D pose reconstruction applied to the reconstruction of the left arm.

of a stationary key point identified in a previous frame is used as the starting point of pin-hole pose reconstruction for the current frame. Walking, as an example, requires that one leg always stays on the ground while the other is swinging and there is a short period of "double support" during which the legs exchange the motion. Therefore the posture can be propagated continuously from one static foot to the other via the "double support" period. This posture propagation can also be used in motions which contain "off-ground" moments (such as running or dancing) where pose interpolation is required to fill the temporal gaps.

The static foot can be identified effectively and accurately by comparing speed of foot points between consecutive frames. Equation 3 makes a tri-nary decision (left foot, right foot or none) of the static foot for the current frame I^t by computing the displacement of the left and right feet between the previous and next frames, I^{t-1} and I^{t+1}. $I^{t-1}_{LF}(x, y)$, $I^{t+1}_{LF}(x, y)$, $I^{t-1}_{RF}(x, y)$ and $I^{t+1}_{RF}(x, y)$ denote the locations of the left and right foot points in the previous and next frames and Euclidean distance is used to compute the displacement between two 2D points. If the displacement of the right foot is greater than the left one, the left foot is determined as the static foot (i.e., $SF(t) = left\ foot$) and vice versa, provided the speed of the foot is below a threshold, Thr.

$$D(t) = \left| I^{t-1}_{LF}(x, y) - I^{t+1}_{LF}(x, y) \right| - \left| I^{t-1}_{RF}(x, y) - I^{t+1}_{RF}(x, y) \right|$$

$$
\begin{aligned}
&If\ (D(t)<0\ \&\&\ |I^{t-1}_{LF}(x, y) - I^{t+1}_{LF}(x, y)|<Thr) \\
&\quad SF(t) = left\ foot \\
&else\ if\ (D(t)>0\ \&\&\ |I^{t-1}_{RF}(x, y) - I^{t+1}_{RF}(x, y)|<Thr) \\
&\quad SF(t) = right\ foot \\
&else \\
&\quad SF(t) = None
\end{aligned}
\qquad (3)
$$

If a static foot is identified, the pin-hole reconstruction (see Section 2.2.2) can be performed for non-key frames. This is a recursive process that propagates the postures from the key frames in both forward and backward directions in time. In each direction, we firstly reconstruct the frame next to the key frames whose static foot 3D position has been identified so that it can be used as a seed of the pin-hole reconstruction for this frame. The reconstruction starts from the static foot 3D point and estimates the 3D positions of the keen and hip of the same leg. It then estimates the 3D position of another leg, and followed by the spin, shoulders, head and arms. Once this frame is reconstructed, its static foot position can be passed on to its adjacent frame that will be reconstructed in the same manner. Since there are multiple key frames within a given sequence, a linear combination of the propagated postures from each key frame is calculated to generate the final one. Weights are introduced to penalise postures which are temporally further away from their key frames.

3 EXPERIMENTAL RESULTS

3.1 Dataset and Experimental Settings

The algorithm was tested on the HumanEva (HE) dataset (http://vision.cs.brown.edu/humaneva), which is used as benchmark for pose recovery. It provides motion capture and video data which were collected synchronously. Therefore, motion capture data provide 3D ground truth of human poses: since cameras are calibrated, 3D data points can be projected on the image plane so that 2D locations of key body points in the sequences are available for pose recovery algorithms. Moreover, a standard set of error metrics is defined to evaluate pose estimations (Sigal and Black, 2006).

To validate our proposed method, two other pose recovery techniques are also evaluated: Reconstruction using orthographic projection (Taylor, 2000),which is one of the most popular 3D pose recovery method for uncalibrated cameras, and pin-hole reconstruction using the calibration data and body model directly provided by the HE. In order to validate the assumption made for our simplified camera model, in the later case, we neglect lens distortion and skew, and set the image centre as the principal centre. To make an unbiased comparison between these two methods and our proposed method, all experiments are conducted with known body ratio (this is obtained from the HE) and known depth relations between pairs of key

points, i.e. front or back, as a substitute for the pose selection.

A sequence of "walking in a circle"-- *S2 Walking (C1)* in the HE-- is selected as a testing sequence. Since the original sequence is quite long, only one complete walking circle is used, i.e. frame 340 to 760. The sequence was chosen to include a variety of walking postures, i.e. a complete circle, seen from different distances and view angles.

3.1.1 Orthographic Reconstruction

This method proposed by Taylor (Taylor, 2000) does not require calibration since it assumes the object to be reconstructed is far away from the camera so that the Z coordinates (the depth) are almost constant for all the points on the object. Since this method requires the user selects a suitable scaling factor, it only recovers the posture (i.e., relative positions of the key body points), but not the actual size of the human subject. Therefore, Procrustes Analysis (Seber, 1984) is performed to facilitate the comparison between the reconstructed body and the motion capture data, which is our ground truth. Procrustes Analysis determines a linear transformation (translation, rotation, and scaling) of the reconstructed body to best match to the ground truth by minimising Root-Mean-Square error (RMS). Reconstruction errors of this method are showed in Figure 6 (blue) and Table 1 (first column).

3.1.2 Pin-Hole Reconstruction using Parameters Supplied from the Dataset

To validate the assumption of the simplified calibration model used in the proposed method, poses are reconstructed using the pin-hole projection model with a number of parameters directly provided from the HE dataset. These include camera calibration parameters, i.e. focal length, camera relative position to a key point of the subject (the shoulder centre), subject's body model and relative depth information of adjacent points. Lens distortion and skew are not considered, and it is assumed the principal axis of the camera goes through the centre of the image. As a result, the pin-hole reconstruction can be seeded from the known shoulder centre. Positions of the other key points are obtained by using projection lines and by taking into account the body model and relative depth information. Procrustes Analysis is performed to allow comparison with motion capture data. The results of this method is showed in Figure 6 (red) and Table 1 (second column)

3.2 Evaluation of Pose Reconstruction

The auto-calibration process identified four key frames, frame 359, 529, 614, 693, within the target walking circle (See Figure 7 for original key frame postures). Thus, their postures were estimated and propagated to other frames using identified static foot points. The final posture estimates are produced by combining propagated poses produced by each key frame as described in Section 2.2.3. Figure 5 shows the RMS errors of propagated postures from each key frame and their combined postures.

Figure 6 and Table 1 show a comparison of our proposed method with the reconstructions described in Section 3.1.1 and 3.1.2. The result of the pose estimation based on manual calibration (Section 3.1.2) produces an average error of 20.5 mm. This validates the assumption of the simplified pin-hole projection model used in our proposed method. Also, since it is manually calibrated, it is considered as the optimal result we could obtain in our method. As shown in Figure 6, our proposed method (black) clearly outperforms the orthographic reconstruction (blue); the average error is reduced by two-third (from 235.8 mm down to 79.5 mm, Table 1). Statistical analysis in Table 1 also indicates our method has reasonable accuracy (average error 79.5 mm) and is consistent (standard deviation is 41.7 mm). We also compare our results with the state-of-the-art; (Husz et al., 2007) worked on similar scenarios (single uncalibrated camera with unspecified action) and an average error of 200 mm was reported. Elgammal and Lee (2006) was able to achieve 30 mm error on tracking joints in the same sequence. However, their method is activity specific (walking) and requires such motion to happen cyclically. Further analysis of reconstruction of each key frame and its posture propagation is shown in Table 2. We notice the reconstruction and propagation of the key frame 693 is significantly worse than other key frames. Since the posture of this key frame is approximately parallel to the image plane (see Figure 7), it results in unreliable coplanar calibration as shown in (Kuo et al., 2007). Moreover, the reconstruction is further deteriorated by lens distortion as the subject is positioned near the border of the image in this frame.

Due to the limited space of the paper, Figure 7 illustrates only a subset of our reconstructed poses against the ground truth. We show the reconstruction of 4 key frames and other poses with a variety of view angles and distances, including the difficult cases where the subject is near the image border or the posture is parallel to image plane.

4 CONCLUSIONS

In this paper, we presented a novel 3D pose recovery algorithm by exploiting human bipedal motion constraints using images from a single uncalibrated camera. The algorithm can estimate camera calibration parameters from a number of frames (i.e., key frames) in the sequence automatically, reconstruct the key frames' postures using a simplified pin-hole camera model and infer postures for other frames. To achieve this, two constraints observed from human bipedal motion were used. One is the coplanarity of the body points in the mid-stance position to perform camera auto-calibration and the other refers to the static point of the foot that allows pose propagation from one frame to next. Our method was validated experimentally. Results showed an accuracy of 8 cm, which is usually sufficient to label poses for action recognition applications.

We plan to use 2D feature detectors and trackers to localise the joints on real video sequences to test further our method against noisy feature locations. We will also incorporate a pose selection module which embeds human motion dynamics and constraints to select the most plausible posture among the generated 3D pose proposals.
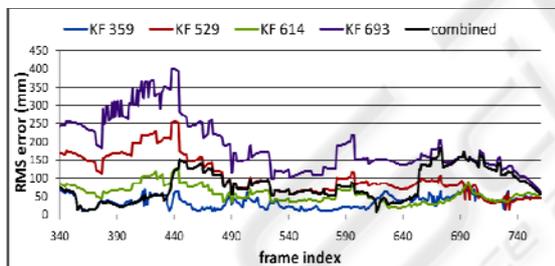
Figure 5: RMS error of our proposed pose recovery algorithm.
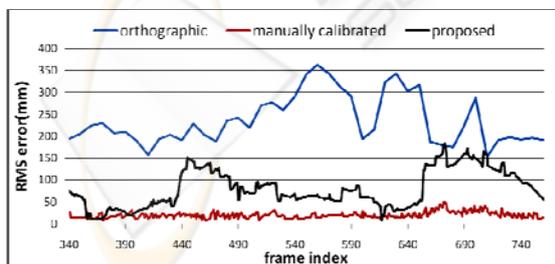
Figure 6: RMS errors of 3 pose reconstruction algorithms.

Table 1: Statistical results of 3 reconstruction algorithms.

error (mm)	ortho-graphic	manually calibrated	proposed
average	235.8	20.5	79.5
max.	363.1	50.0	182.8
min.	153.3	8.0	7.4
s.d.	57	6.9	41.7

Table 2: Statistical results of key frame reconstruction and propagation.

key frame	reconstruction error (mm)	Average error (mm) in propagation
359	23.0	35.5
529	67.4	106.3
614	46.3	58.0
693	172.4	189.6

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Frame 359 (rms =23.0)	Frame 529 (rms =67.4)	Frame 614 (rms =46.3)	Frame 693 (rms =172.4)	Frame 393 (rms =21.2)	Frame 450 (rms = 143.3)	Frame 555 (rms = 62.6)	Frame 653 (rms = 54.7)	Frame 742 (rms = 92.9)
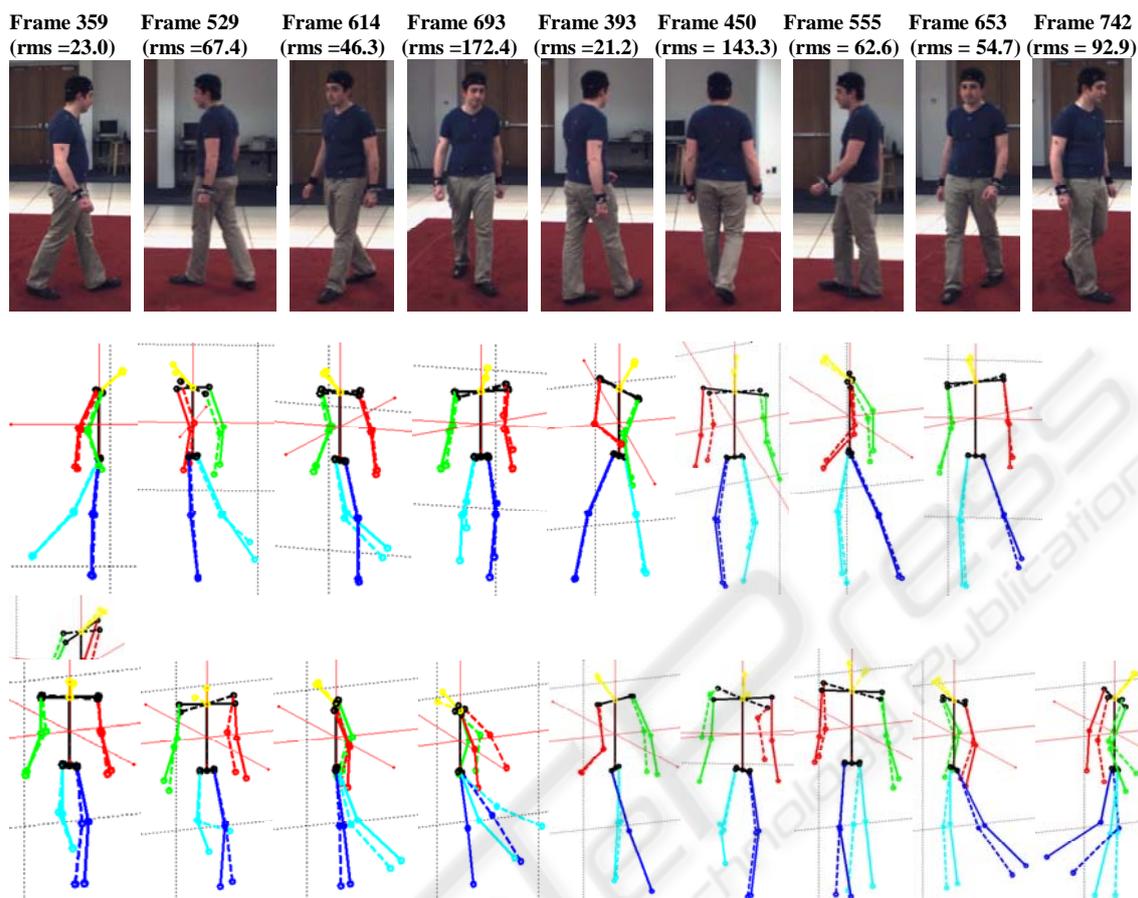
Figure 7: Reconstruction results; first row: frame index; second row: associated posture error, (Root-Mean-Square error in mm); third row: original images; forth row: reconstructed (solid) and ground truth (dotted) postures observed from the original viewpoint; fifth row: reconstructions observed from a novel viewpoint. The first 4 images are the key frames; Frame 693 and 450 show poor reconstructions where the subject is located near the borders of the image.

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