A Factorization-based Approach to Articulated Motion Recovery

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Abstract

This paper addresses the subspace properties and the recovery of articulated motion. We point out that the global motion subspace of an articulated object is a combination of a number of intersecting rigid motion subspaces of the parts. Depending on whether a link of two parts is a joint or an axis, the global motion subspace loses one or two in rank for each link. The rank loss results from the intersection between the rigid motion subspaces of linked parts. Furthermore, the intersection is, in fact, the motion subspace of the link. From these observations, we describe the rank constraint of the global motion subspace of an articulated object; we give an algorithm to recover the image motion of a link, either a joint or an axix; and we propose a novel but simple approach, which is based on subspace clustering, to recover articulated shape and motion from a single-view image sequence.

1. Introduction

Shape and motion recovery deals with the problem of estimating the scene geometry and camera motion. It has a wide variety of applications in robotics, navigation, 3D modeling and animation, etc.

One type of approaches that has proven very versatile is factorization-based. By studying the intrinsic properties of the motion subspace of the scene, shape and motion can be factorized directly from image motion data. Tomasi and Kanade [1] first pointed out that the rank of the motion subspace of a rigid scene under orthographic projection is at most 4. Using a factorization method, rigid shape and motion are robustly recovered. Later work Poelman and Kanade [2] extends the factorization method to a paraperspective camera model, an approximation of a perspective camera. Under this model, the motion subspace of a rigid scene remains at most of rank 4. Costeira and Kanade [3] shows that the motion subspace of independently moving objects are orthogonal to each other. This property makes possible a segmentation of the motion subspaces of different objects through a constructed shape interaction matrix. After the segmentation, shape and motion of each object can be recovered independently. It is important to notice that when motions are not independent (as for the articulated case), the property of orthogonality does not exist any more and this algorithm is not applicable. In Han and Kanade [4], it is shown that the motion subspace of linearly moving objects is at most of rank 6 without regard to the number of objects. The motions of the objects can be recovered from this motion subspace by a linear algorithm. Bregler et al. [5] shows that the motion subspace of a nonrigid shape can be approximated by a linear combination of a certain number of key shapes. Using a factorization method combined with nonlinear iterations, shape and motion of a nonrigid scene may be recovered. Further refinements of this approach were proposed in [11, 12, 13, 10].

To our knowledge, the property of an articulated motion subspace has not been studied in detail in the literature. In this paper we point out that the nature of the motion subspace of an articulated object is a combination of a number of intersecting rigid motion subspaces. Furthermore, we derive two intrinsic properties of this subspace. One is that the largest possible rank of the global motion subspace is less than the sum of that of each articulated part. The correlation of the subspaces of two linked parts results in one respectively two ranks lost for a joint link and an axis link. The second property is that the rank loss results from an intersection between the motion subspaces of the linked parts; this subspace intersection has a physical meaning: it is the motion subspace of the joint or the axis. These properties allow us to automatically detect the type of a link and recover the motion of a link from the intersection. We propose algorithms to do that.

Another advantage of viewing the global motion subspace of an articulated object as a combination of intersecting motion subspaces is that it inspires a new and simple strategy to recover articulated shape and motion which is based on clustering and segmenting motion subspaces. Any robust reconstruction method of a rigid object can then be applied to each segmented subspace. By putting together the individual parts into the same coordinate system, e.g. the camera coordinate, the articulated shape and motion get recovered.

Other researchers have been working on algorithms to compute articulated shape and motion; some of them use factorization-based methods as well. The originality of this paper lies in our perspective of viewing articulated motion as a set of intersecting motion subspaces and our recovery approach, whose simplicity benefits from this perspective and which only requires basic operations such as subspace intersection, clustering and segmentation. We summarize others' works in the following and make comparison with ours. In Zhou et al. [8] each part of an articulated object is treated as independently moving objects using Costeira and Kanade [3]'s approach at the initial stage and then apply translation constraint on top of it. During the process, the root object needs to be recovered first and then the rest is solved hierarchically. An important issue is that articulated shapes do not satisfy the orthogonality assumption of [3]. In our approach, the articulated parts are treated equally as different intersecting subspaces and no heuristics are needed. The translation constraint is intrinsically expressed in the intersection of motion subspaces and does not need to be imposed explicitly. The approach proposed in Sinclair et al. [9] first needs to recover the projective structure including the rotation of the camera before they can use a minimization approach to recover an axis and the joint case is not addressed. Our method directly achieves the motion subspace of an axis or joint from the image measurement data without carrying out any prior shape recovery.

There are also a large group of articulated motion tracking research that is based on fitting a prior model with image data [14, 15, 16, 17]. Our approach doesn't require such a prior model as the articulation model is inferred from the data, but could potentially be used to construct prior models for those approaches.

The remainder of this paper is organized as follows. Section 2 discusses the rank constraints of the articulated motion; Section 3 gives the algorithms to compute the image motion of an axis or joint by intersecting motion subspaces of articulated parts; Section 4 overviews our approach to recover articulated shape and motion; Section 5 discusses the experimental results; Section 6 draws the conclusion and describes future work.

2. Subspace Properties of Articulated Motion

In this section, we introduce the rank constraints of different motions from a rigid object to independently moving objects. Then, we derive the rank constraint of the articulated motion and describe the relationship between the motion subspace of a link and the intersection of the motion subspaces of two linked parts. Our discussion is based on orthographic cameral model.

2.1. Rank constraint of the rigid motion subspace

The motion matrix W is a set of n tracked feature points of a rigid body across a number of f frames:

$$W = \begin{pmatrix} u_{1,1} & u_{1,2} & ... & u_{1,n} \\ v_{1,1} & v_{1,2} & ... & v_{2,n} \\ ... & ... & ... & ... \\ u_{f,1} & u_{f,2} & ... & u_{f,n} \\ v_{f,1} & v_{f,2} & ... & v_{f,n} \end{pmatrix} \quad (1)$$

The coordinates $(u_{i,j}, v_{i,j})$ represent the location of feature point j in frame i. The homogeneous world coordinates of these feature points are represented by S which we call the shape matrix:

$$S = \begin{pmatrix} x_1 & x_2 & ... & x_n \\ y_1 & y_2 & ... & y_n \\ z_1 & z_2 & ... & z_n \\ 1 & 1 & 1 & 1 \end{pmatrix}$$

M is the camera rotation matrix over all the frames and M_i is a 2×3 projection matrix for the i^{th} frame.

$$M = \begin{pmatrix} M_1 & M_2 & ... & M_f \end{pmatrix}^T$$

T is the camera translation vector over all the frames.

$$T = \begin{pmatrix} t_1^x & t_1^y & ... & t_f^x & t_f^y \end{pmatrix}^T$$

W, M, T and S are related by:

$$W = (M|T)S$$

So the motion matrix W of a rigid object is at most of rank 4.

2.2. Rank constraint of the motion subspace of independently moving objects

Similar to (1), now the n tracked feature points of W belong to independently moving objects. Suppose these tracked points are grouped by the object that they belong to. Suppose there are m objects and their shape matrices are S_1, ..., S_m. Their motion matrices and translation vectors are M_1,...,M_m and T_1,...,T_m respectively. The relation of these matrices is:

$$W = (M_1|T_1|M_2|T_2|...|M_m|T_m) \begin{pmatrix} S_1 & & \\ & ... & \\ & & S_m \end{pmatrix}$$

W is at most of rank $4 \times m$. For sufficiently general shape and motion, the rank of W is exactly $4 \times m$. Note that $(M_i|T_i)$ corresponds to the relative motion between the object and the camera. While the camera motion is shared for all the objects, in this case the object motion is independent for each object.

2.3. Subspace properties of the global motion subspace of an articulated object

Given a set of n feature points tracked across a number of f frames belonging to an articulated object consisting of m parts, the rank of W is smaller than $4 \times m$. In general, each link results in 1 or 2 ranks lost. This will be shown as followed.

2.3.1 Rank constraint of two linked articulated parts of the object

For simplicity, we will initially represent the relative motion between two parts as a deformation of the shape in the following section. Without loss of generality, we assume the object-camera motion is expressed relative to the coordinate system of the first part. We further assume that when the link is an axis, the z-axis of the object coordinate system coincides with the axis; when the link is a joint, the origin coincides with the joint. Thus, for the i^{th} frame, the shape of the other part can be expressed relative to the first part.

$$S_{2i} = \begin{pmatrix} R_i & 0 \\ 0 & 1 \end{pmatrix} \cdot S_1$$

where R_i can be any 3×3 rotation matrix when the link is a joint and

$$R_i = \begin{bmatrix} \cos\theta_i & \sin\theta_i & \\ -\sin\theta_i & \cos\theta_i & \\ & & 1 \end{bmatrix} \quad (2)$$

when the link is an axis.

Let W_i be the image coordinates of the i^{th} frame in the motion matrix W.

$$\begin{aligned} W_i &= (M_i|T_i|M_i|T_i) \begin{pmatrix} S_1 & \\ & S_{2i} \end{pmatrix} \\ &= (M_i|T_i|(M_i \cdot R_i)|T_i) \begin{pmatrix} S_1 & \\ & S_2 \end{pmatrix} \end{aligned}$$

- For an axis, besides two identical T_i, it is easy to see from (2) that the last columns of M_i and $M_i \cdot R_i$ are identical too. So $(M_i|T_i|(M_i \cdot R_i)|T_i)$ $(i = 1, 2, ..., f)$ is of at most rank 6. Thus, the motion matrix W is of at most rank 6.
- For a joint, $(M_i|T_i|(M_i \cdot R_i)|T_i)$ $(i = 1, 2, ..., f)$ is at most of rank 7 because R_i can be any 3×3 rotation matrix. Thus, W is of at most rank 7.

To summarize, a joint link results in 1 rank lost and an axis, 2 rank lost.

2.3.2 The intersection of the subspaces of two linked parts

Each articulated part is basically a rigid body and has a motion subspace of at most rank 4. The motion matrix of two linked parts loses 1 or 2 ranks, which implies that the subspaces intersect. When the link is a joint, the 1-dimensional intersection is the motion subspace of the joint. For an axis, the 2-dimensional intersection is the motion subspace of the axis. We provide the proof in the following. We assume for simplicity that the shape and motion are not degenerate though the same result holds for degenerate cases.

Suppose the motion matrices of the two parts are W and V. W_i and V_i are the rows in W and V corresponding to frame i. We have:

$$W_i = (M_i|T_i)S_1 \quad (3)$$

$$V_i = ((M_i \cdot R_i)|T_i) \cdot S_2 \quad (4)$$

- For the joint case, the rank of $(W|V)$ is 7. That is one rank less than the sum of the ranks of W and V. So the intersection between their subspaces should be of rank 1.

  Next, we are going to show that the trajectory of the joint over all frames is in both subspaces of W and V so that the intersection is indeed the motion subspace of the joint.

  The trajectory of the joint over all frames is:

  $$J = \begin{pmatrix} T_1 \\ ... \\ T_f \end{pmatrix}$$

  When the shape S_1 is not degenerate, there exists a linear combination $S_1 \cdot C = (0, 0, 0, 1)^T$(Notice that when S_1 is a planar or linear shape, this condition is still satisfied if the joint is within that plane or line). So $W_i \cdot C = (M_i|T_i)S_1 \cdot C = T_i$. This proves that J is in the subspace of W. Similarly, we can prove that J is also in the subspace of V.

- For the axis case, the rank of $(W|V)$ is 6. So the intersection is of rank 2.

  Next, we need to show that the trajectory of the axis is of rank 2 and is in both subspaces of W and V so that the intersection is indeed the motion subspace of the axis.

  We represent the axis trajectory as a span of the trajectories of two points on the axis, whose object coordinates are $(0, 0, 0, 1)^T$ and $(0, 0, 1, 1)^T$. So these two trajectories are:

  $$A_{(0,0,0,1)^T} = \begin{pmatrix} T_1 \\ ... \\ T_f \end{pmatrix}$$

$$A_{(0,0,1,1)^T} = \begin{pmatrix} M_1^{(.3)} \\ ... \\ M_f^{(.3)} \end{pmatrix} + \begin{pmatrix} T_1 \\ ... \\ T_f \end{pmatrix}$$

$M_i^{(.3)}$ represent the last column of M_i. It is easy to see that they span a rank 2 subspace.

Following a similar argument in the joint case, we can prove that $A_{(0,0,0,1)^T}$ and $A_{(0,0,1,1)^T}$ are in the subspaces of both W and V.

3. Finding axes and joints in articulated motion

We provide our algorithm to find the motion subspace of the link in this section.

Let W_1, W_2 be the motion matrices of two linked parts. We assume for simplicity that there is no degenerate motion and shape, i.e. $rank(W_1) = rank(W_2) = 4$, but similar derivations can also be made for lower dimensional subspaces corresponding to planar and linear object or object parts. As discussed in Section 2.3.1, $rank(W_1|W_2) = 6$ for the case of an axis and $rank(W_1|W_2) = 7$ for the case of a joint.

3.1 Finding the axis

3.1.1 The intersection of W_1 and W_2

Using singular value decomposition (SVD), we can decompose $W_1 = U_1 \cdot \Sigma_1 \cdot V_1{}^\top$ and $W_2 = U_2 \cdot \Sigma_2 \cdot V_2{}^\top$. $\tilde{U}_i$ represents the first 4 columns of U_i. Let N represent the two right null vectors of $(\tilde{U}_1|\tilde{U}_2)$, so that

$$(\tilde{U}_1|\tilde{U}_2) \cdot \begin{bmatrix} N_1 \\ N_2 \end{bmatrix} = 0 \Rightarrow \tilde{U}_1 \cdot N_1 = -\tilde{U}_2 \cdot N_2 \qquad (5)$$

Let $T = \tilde{U}_1 \cdot N_1 = \tilde{U}_2 \cdot -N_2$. Therefore, the subspace T represents the intersection of the subspaces W_1 and W_2.

3.1.2 The constraint of the motion subspace of a point on the axis

While it is a necessary condition for trajectories of points on the axis to be in the subspace T, it is not a sufficient condition. Inside this 2D subspace only a 1D linear space corresponds to trajectories of 3D points. This is the same as the 3D space of possible trajectories embedded in the 4D subspace as discussed in [3]. A particular trajectory inside the 2D subspace T can be represented by $t(\alpha, \beta) = T \begin{bmatrix} \alpha \\ \beta \end{bmatrix}$.

If $W_1^* = W_1 - \bar{W}_1 \cdot [1 \cdots 1]$ with $\bar{W}_1$ the average of all the trajectories, then the rank of W_1^* is 3 [1]. For the trajectory $t(\alpha, \beta)$ to correspond to a 3D point rigidly attached with the first shape, the matrix $W_{1t}^* = (W_1^* | t(\alpha, \beta) - \bar{W}_1)$ should also have rank 3.

Given the SVD of $(W_1^* | - \bar{W}_1) = \tilde{U}_{1*} \tilde{\Sigma}_{1*} \tilde{V}_{1*}^\top$ limited to the four non-zero singular values and $\tilde{V}_{1*}^{((n+1)\cdot)}$ the last column of $\tilde{V}_{1*}$,

$$\begin{aligned} |\det W_{1t}^*| &= |\det(\tilde{U}_{1*}\tilde{\Sigma}_{1*}\tilde{V}_{1*}^\top + (0|T \begin{bmatrix} \alpha \\ \beta \end{bmatrix})| \\ &= |\det(\tilde{\Sigma}_{1*} + \tilde{U}_{1*}^\top T \begin{bmatrix} \alpha \\ \beta \end{bmatrix} \tilde{V}_{1*}^{((n+1)\cdot)})| \ . \end{aligned}$$

Using the multilinear properties of determinants and introducing the notation $\tilde{\Sigma}_{1*} = (A_1|A_2|A_3|A_4)$ and $\tilde{U}_{1*}^\top T \begin{bmatrix} \alpha \\ \beta \end{bmatrix} \tilde{V}_{1*}^{((n+1)\cdot)} = (Bv_1|Bv_2|Bv_3|Bv_4)$, we obtain the following constraint:

$$\begin{aligned} &\det \Sigma_{1*} + \det(Bv_1|A_2|A_3|A_4) + \det(A_1|Bv_2|A_3|A_4) \\ &\quad + \det(A_1|A_2|Bv_3|A_4) + \det(A_1|A_2|A_3|Bv_4) = 0 \end{aligned} \qquad (6)$$

Note that this constraint is linear in α and β as all higher order terms disappear due to linearly dependent columns.

3.2 Finding the joint

The computation of the trajectory of a joint can be done in a similar fashion. In this case the nullspace N in (5) is only represent by a single nullvector and the subspace T representing the intersection of W_1 and W_2 is one dimensional. Inside this subspace only a single point corresponds to the trajectory of a real 3D point, this is the joint. Using $t(\alpha) = T\alpha$ in (6) we now obtain a linear equation for α which allows us to obtain the joint.

4. Articulated Motion Recovery

We summarize our approach to recover articulated motion from a single-view image sequence in this section. We assume the shape and motion is general. Degenerate cases are briefly discussed in Section 6.

4.1 Tracking

We use a KLT tracker to track features in image sequences and build the motion matrix.

With prior knowledge of the object, we can derive and impose the rank constraint of the articulated motion directly to the motion matrix. Without that knowledge, we propose to detect an effective rank k (Section 4.4) of the motion matrix.

We can reject outliers based on the rank constraint . We iteratively reject a column, i.e. one feature trajectory, that deviates from the constrained motion subspace most, and reimpose the rank constraint on the raw data of the remaining features until the largest deviation is below a certain threshold.

4.2 Subspace Clustering

The global motion subspace of an articulated object is a mixture of intersecting subspaces of the parts. We use Generalized Principle Component Analysis(GPCA) to compute these subspaces and segment the feature trajectories. GPCA is an algorithm to compute a mixture of linear subspaces from a data set and then segment the data according to the underlying linear subspaces. Further details can be found in [6] and [7].

Each subspace of an articulated part is of rank 4 in general, we project all feature trajectories onto a rank-5 subspace. GPCA can identify the number of the hyperplanes(subspaces of rank 4 in this case), compute the hyperplanes from the projected trajectories, and segment those trajectories.

4.3 Shape and Motion Recovery

Each group of segmented trajectories belongs to an articulated part. By imposing the rigidity constraint [1], we can carry out a second outlier rejection process within each group. A robust rigid motion recovery algorithm [1, 2] then can be used to recover the shape and motion of each part.

Furthermore, by intersecting the subspaces of each group of trajectories and detecting the ranks (Section 4.4) of the intersection we can induce whether two parts are linked and, if so, whether the link is an axis or a joint. Rank 0 indicates no link; rank 1, a joint link; rank 2, an axis link. Then the shape and motion of the axis or joint can be recovered accordingly.

4.4 Effective Rank Detection

In practice, the motion matrix is corrupted by noise and outliers and thus its rank is usually full. Without prior knowledge of the scene and object, we may use a model selection algorithm inspired by a similar one in [7] to detect an effective rank.

$$r_n = \text{arg min}_r \frac{\lambda_{r+1}^2}{\sum_{k=1}^{r} \lambda_k^2} + \kappa\, r$$

with λ_i the i^{th} singular value of the matrix and κ a parameter. If the sum of all λ_i^2 is below a certain threshold, the effective rank is 0.

5. Experiments

In the first experiment, a toy truck with a moving shovel is videotaped. A KLT tracker successfully tracks 99 features over 70 frames while the truck moves and the shovel rotates along an axis on the truck. 87 features are left after the first outlier rejection using the rank constraint of the articulated motion. The GPCA algorithm identifies two subspaces from the feature trajectories and segment the trajectories accordingly (Figure 1).

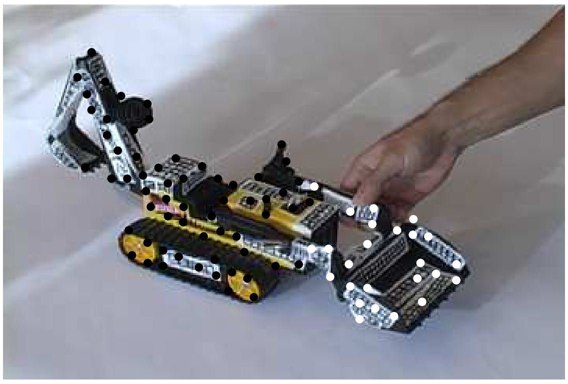

Figure 1. The GPCA algorithm identifies two subspaces from the feature trajectories and segments them accordingly. The color of a feature shows the subspace it belongs to

74 features remain after the second outlier rejection using the rigidity constraint of each part. An axis is identified by intersecting the motion subspaces of the articulated parts. Its image positions are recovered using our algorithm (Figure 2).

Each articulated part can be recovered as a rigid shape using the factorization method [1]. By putting all parts into the camera coordinates, shape and motion of the articulated object gets recovered. Furthermore, with the axis recovered in the camera coordinates, we can reanimate the articulated motion by rotating a part around the axis and generate not only novel views but also novel motions (Figure 3).

In the second experiment, a person moving his upper body and head is videotaped. 99 features over 60 frames are tracked while the upper body moves and the head rotates around the neck. 93 features are left after the first outlier rejection. The GPCA algorithm identifies two subspaces from the feature trajectories and segment the trajectories accordingly (Figure 4). 92 features remain after the second outlier rejection. The articulated joint is identified (Figure 5).

6. Conclusions and Future Work

We have shown that the subspace of articulated motion is a set of intersecting rigid motion subspaces. We have derived the rank constraint of articulated motion and proved that the intersection of the motion subspaces is the motion subspace of an axis or a joint. We demonstrate a factorization-based approach to articulated motion recovery based on subspace clustering. The articulated shape and

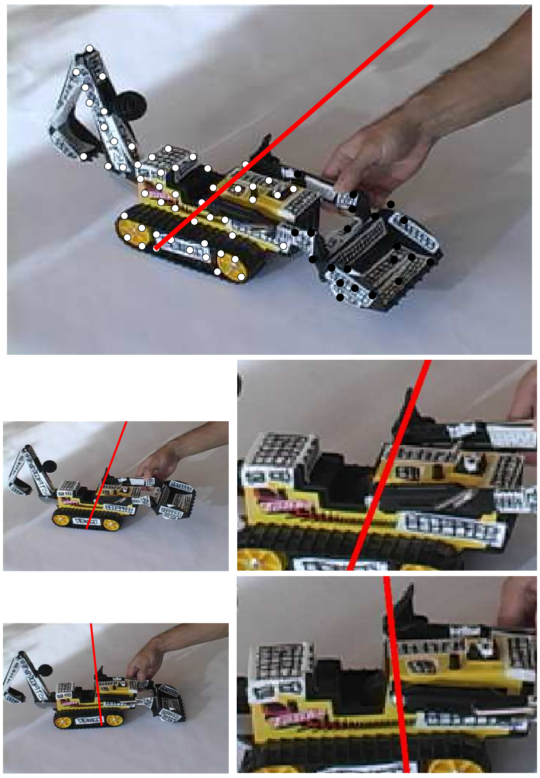

Figure 2. (top) An axis is identified by intersecting the motion subspaces of the articulated parts. (middle and bottom) The recovered axis in two frames are shown.

motion, as well as the axes and joints, can be recovered using our approach.

In the future, we intend to deal with missing data in the motion matrix using the rank constraint of articulated motion. And we need a more robust rank detection algorithm so that we can handle degenerate shapes and motions. We also intend to extend our approach to more complex objects and motions, e.g. human motion. Besides handling more parts of an articulated object, there is a possibility of combining our approach with factorization-based nonrigid-shape-from-motion approaches. The combination should be more powerful to handle human motion in general.

Acknowledgments

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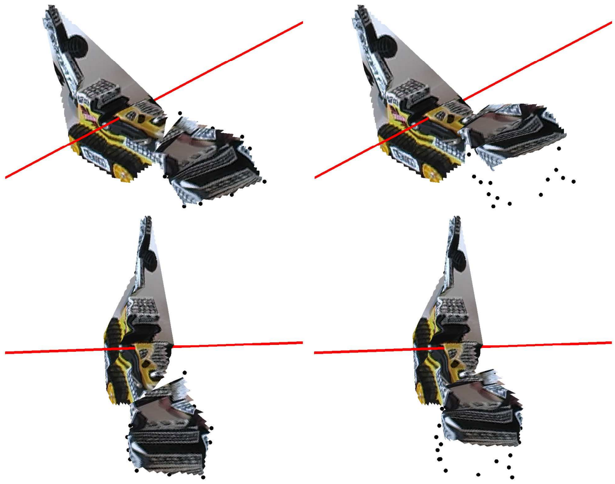

Figure 3. The shape and motion of the truck get recovered and reanimated. The black dots show the original position of the shovel. Not only novel views but also novel motions can be generated by rotating the shovel around the axis.

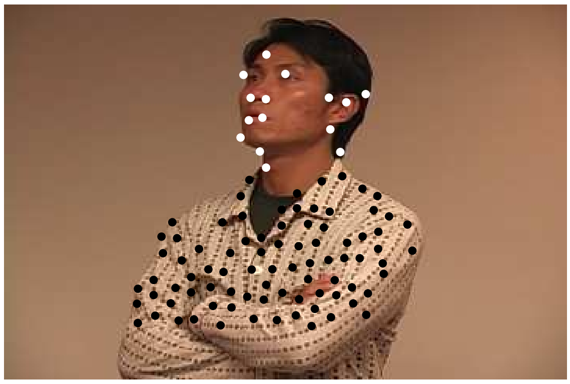

Figure 4. The GPCA algorithm identifies two subspaces from the feature trajectories and segments them accordingly. The color of a feature shows the subspace it belongs to

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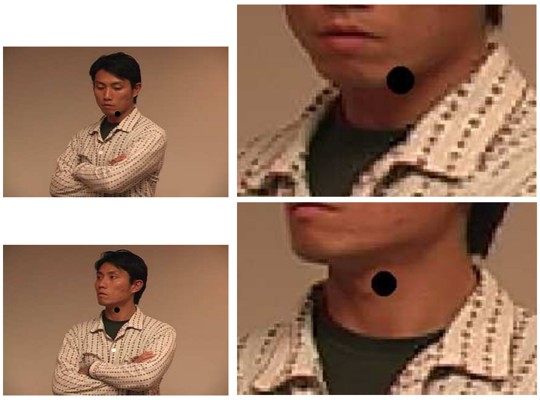

Figure 5. A joint is identified by intersecting the motion subspaces of the articulated parts. The recovered joint in two frames are shown.

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