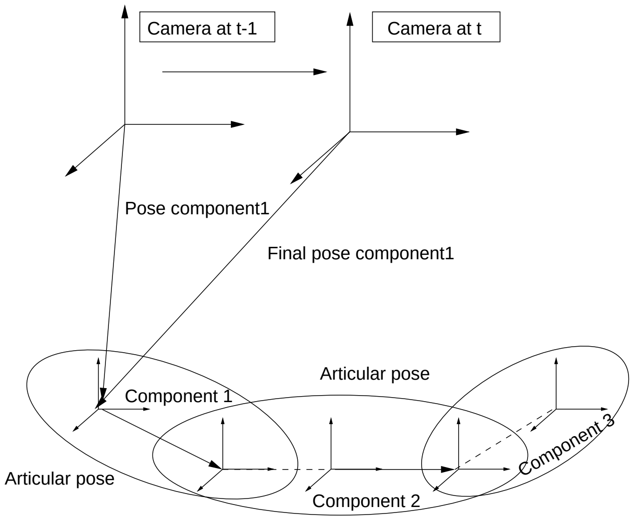
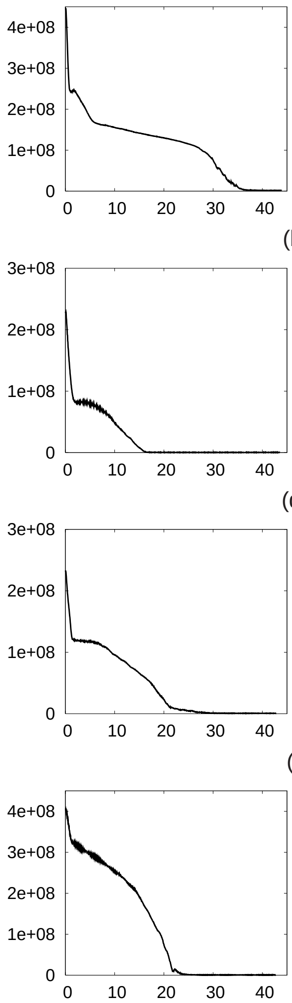


Figure 1: Kinematic chain method: The pose of an articulated object is determined via a kinematic chain of rigid bodies extending to subcomponents.



(a) (b)

(c) (d)

(e) (f)

(g) (h)

Fig. 5.4 Second experiment. Same positioning task with respect to various objects. Objects considered (left column) and cost functions (right column) (x axis in seconds).

positioning error, and thus the camera trajectory, are really not affected by the occlusions. This very nice behavior is due to the high redundancy of the visual features we use.

where ${}^aR_b$ is a rotation matrix between frames and ${}^at_b$ a translation vector between frames which are obtained from ${}^ar_b$. $[t]_\times$ is the skew symmetric matrix related to t.

The projector defined in (10) is applied in the joint reference frame. It is possible to choose the object frame as a common reference frame as in [3]. In this paper the camera frame is chosen as the common reference frame so that a generic subspace projection operators J_l and $J_l^\perp$ can be defined as:

$$
\begin{aligned}
J_l &= Im({}^cV_l P_l {}^lV_c);\\
J_l^\perp &= Ker(J) = Im({}^cV_l P_l^\perp {}^lV_c);
\end{aligned}
\tag{13}
$$

where Im represents the Image operator which reduces the column space to its mutually independent basis form. The first transformation V maps the velocities to the joint frame l and the second re-maps back to the camera reference frame.

3.4 Articulation Matrix

Using the previous joint definition is is possible to define the Articulation matrix according to equation (4) and taking into account the joint subspaces given by equation (13).

The derivation of the Articulation matrix corresponds to:

$$
A = \begin{pmatrix} \frac{\partial \delta_1}{\partial q} \\ \vdots \\ \frac{\partial \delta_m}{\partial q} \end{pmatrix};
\tag{14}
$$

where m is the number of components.

For an object with two components and one joint and using the orthogonal subspace projectors given in equation (13), A is given by:

$$
A = \begin{pmatrix} \frac{\partial \delta_1}{\partial q_\cap} & \frac{\partial \delta_1}{\partial q_1} & 0 \\ \frac{\partial \delta_2}{\partial q_\cap} & 0 & \frac{\partial \delta_2}{\partial q_2} \end{pmatrix} = \begin{pmatrix} J_1 & J_1^\perp & 0 \\ J_1 & 0 & J_1^\perp \end{pmatrix};
\tag{15}
$$

where $q_\cap$, q_1, q_2 are vectors representing the sets of intersecting velocities and each components free parameters respectively. These sets are easily identified when referring to Figure 3. Given $\dim(J_1) = 6 - c$ and $\dim(J_1^\perp) = c$, the mapping A is indeed dimension $12 \times (6 + c)$, remembering that c is the class of the link. The derivation of objects with more than one joint follows in a similar manner and is left to the reader.

It is important to note that this method introduces decoupling of the minimization problem. This is apparent in equation (15) where extra zeros appear in the Jacobian compared to the traditional case of a kinematic chain. Indeed, in the particular case of two components and one articulation a kinematic chain has only one zero.

4 Registration

In this section a new tracking

Y

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