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Video image inpainting using posture mapping

P.Indumathi

ABSTRACT

Department of Electronics Engineering, Anna University, Chennai, TamilNadu, India.

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Keywor ds

Posture mapping, Synthetic posture, Key postures, Video inpainting. complete an object, first samples a 3-D volume of the video into directional spatio – temporal slices, and then performs patch-based image inpainting to repair the partially damaged object in the 2-D slices. The slices are combined to obtain a sequence of virtual contours of the damaged object. The virtual contours and a posture sequence retrieval technique are then used to retrieve the most similar sequence of object postures in the available non-occluded postures. Key-postures selection and indexing are used to reduce the complexity of posture sequence. A synthetic posture generation scheme that enriches the collection of key-postures so as to reduce the effect of insufficient key-postures.

A novel framework for object – based video inpainting is presented in this paper. To

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Introduction Video Inpainting

Video inpainting has attracted great attention in recent years due to its powerful capability in fixing/restoring damaged videos. In recent years, a number of methods have been proposed. These methods can be classified into two types patchbased, and object-based. The proposal of a video inpainting technique which combines motion vector and image inpainting together to perform video inpainting. Three mosaics including the background, the foreground and the optical-flow, are constructed based on motion vector to provide information for video inpainting. This patch-based approach produces good visual, but it cannot maintain continuity along the temporal axis. using a fixed-sized cube as the unit of similarity measure. For each missing pixel, a set of constituent cubes are used to calculate the value of a missing pixel. To save computation time, a multi-scale approach is adopted. The process starts at the coarsest pyramid level and the solution is propagated to finer levels for further refinement. Although the result reported in is good, only low resolution videos are shown and the multi-scale nature may cause over-smoothing artifacts and high computation complexity. Shenet proposed to construct motion manifolds of the space-time volume. The constructed motion manifolds contain the entire trajectory of pixels.

Object Inpainting Scheme

In this paper, a new object-based video inpainting technique that can tackle simultaneously the problems of spatial consistency, temporal continuity, over-smoothing artifact, and insufficiency of available postures. The Architecture of the proposed object completion scheme, which involves three steps: virtual contour construction, key posture-based posture sequence matching, and synthetic key posture generation. The first step of object inpainting involves sampling a 3-D volume of video into directional spatio-temporal slices. Then a patch-based image inpainting scheme is performed to complete the partially damaged object trajectories in the spatio-temporal slices.

The completed spatio-temporal slices are then combined to form a sequence of virtual contours of the target object. Next, the derived virtual contours and a posture sequence matching technique are used to retrieve the most similar sequence of object postures from among the available non-occluded postures. The available postures are collected from the nonocclusion part of the input video. We perform key posture selection, indexing, and coding to convert the posture sequence retrieval problem into a substring search problem If a virtual contour cannot find a good match in the database of available postures, we construct synthetic postures by combining the constituent components of key postures to enrich the posture database so as to mitigate the problem of insufficient available postures. After retrieving the most similar posture sequence, the occluded objects are completed by replacing the damaged objects with the retrieved ones.



Fig.1 Architecture of object completion scheme Object completion using posture mapping

To make an object completion process visually, it is important to extract, from a damaged object in consecutive frames, a set of features that not only represents the object's characteristics i.e., shape, appearance, and posture but also takes into account the temporal motion continuity. The use of spatiotemporal slices to compose virtual object contours and then use them as the features to guide the object completion process. After object extraction and removal, sample a 3-D video volume which is composed of a number of contiguous frames. then obtain a set of directional 2-D spatio-temporal slices which an fully capture an object's motion if the object only has horizontal motions. As shown in Fig.2 after removing the foreground object, object occlusions result in incomplete trajectories of an object in the XT slices. These missing regions need to be completed before composing a virtual contour.



Fig 2 construction of virtual contour mapping Key-posture selection and posture mapping Virtual contour

After obtaining virtual contours, the contours are subsequently used for matching the most similar postures from the set of available postures to complete the occluded objects. The method first uses the key-posture selection method proposed to select the most representative postures out of the available postures. This method uses a set of feature points to describe an object's silhouette. A convex hull bounding the silhouette which are more important than the others as key feature points to describe the shape context of the object.

$$H(\pi) = \sum_{j \neq \lambda} C(p_j, q_{\pi(j)})$$
(1)
$$C(p_i, q_j) = \frac{1}{2} \sum_{k=1}^{K} \frac{\left[h_i(k) - h_j(k)\right]^2}{h(k) + h_j(k)}$$
(2)

where H(S) represents the similarity between two posture silhouettes. C(pi,qj) represents the similarity between two feature points pi and qj, and hi(k). hj(k) denote the corresponding histograms of pi and qj, respectively. A posture is selected as a key posture, if its degree of similarity with all key postures exceeds a predefined threshold, THp. After the key posture selection process, each key posture is labeled with a unique number. Each available posture and virtual contour are then matched with the key posture that has the most similar context. If a virtual contour cannot be matched in this way, it is given a special label. As a result, a sequence of contiguous available postures and virtual contours can be converted into a string of key-posture labels based on the temporal order, as shown in Fig. 3.



Fig. 3 converting virtual contours into a sequence key posture labels.

Synthetic Postures Generation

The occlusion problem occurs in real-world applications all the time; hence, a virtual contour generated from an occlusion event may not find a good match among the selected key postures due to the lack of available non-occluded object postures. The problem of insufficient postures usually arises when the occlusion period for a to-be-completed object is long, resulting in many reconstructed virtual contours, or when the object's non-occlusion period is too short to collect a sufficiently rich set of non-occluded postures. Using a poorly matched posture to complete an occluded object can result in visually annoying artifacts. To resolve the problem where a virtual contour cannot find a good-match in the available key-posture database, synthesize more postures by combining the constituent components of the available postures to enrich the content of the database.



Fig 4 synthesizing new postures using available postures.

In Fig. 4 shows how a new posture is synthesized by using three constituent components (the head, body, and legs) from different available postures selected by a skeleton matching process. The above mentioned constituent components that can be used to synthesize a new database posture all come from the components of existing database postures. To use these components, need to perform segmentation on those database postures in advance. alignment postures, we compute the difference between every consecutive key posture pairs. From the distribution of the variances, one is able to identify what parts are moving most frequently. We then label these "frequently moving" components as the constituent components of a key posture synthesis process.

Results

In the experiment, the five test sequences to test the effectiveness of the method. Among these sequences, the first three were captured by a commercial digital camcorder with a frame rate of 30 fps, and a resolution of 352×240 (SIF). The remaining two test sets were taken, respectively, from 1 and 3.





As shown in Fig.5(a), the sequence to compare the performance of the proposed method with that of the method proposed 1. The inpainting result for test sequence 4 provided shows flickering artifacts at the boundaries of both the original and the inpainted objects due to transitions that are not smooth, even though the inpainted object looks good in individual frames using available postures to complete damaged objects, insufficient available postures reduces the accuracy of inpainting. As mentioned earlier, the proposed synthetic posture generation scheme can maintain the motion continuity of the object effectively.

Conclusion

In this paper, the proposed novel method for completing an occluded object. The method involves three major steps: virtual contour construction, key posture-based sequence retrieval, and synthetic posture generation. The propose of an efficient posture mapping method that uses key posture selection, indexing, and coding to convert the posture sequence retrieval problem into a substring matching problem. The develop of a synthetic posture generation scheme that enhances the variety of postures available in the database. The experimental results show that the proposed method generates completed objects with good subjective quality in terms of the objects' spatial consistency and temporal motion continuity.

References

[1] K. A. Patwardhan, G. Sapiro, and M. Bertalmío, "Video Inpainting under constrained camera motion," IEEE Trans. Image Process., vol. 16, no. 2, pp. 545–553, Feb. 2007

[2] Y. Wexler, E. Shechtman, and M. Irani, "Space-time completion of video," IEEE Trans. PAMI, vol. 29, no. 3, pp. 1–14, Mar. 2007

[3] S.-C. S. Cheung, J. Zhao and M. V. Venkatesh, "Efficient object-based video inpainting," IEEE Conf. Image Process., pp. 705–708, 2006.

[4] J. Jia, Y.-W. Tai, T.-P. Wu, and C.-K. Tang, "Video repairing under variable illumination using cyclic motions," IEEE Trans. PAMI., vol. 28, no. 5, pp. 832–839, May 2006.

[5] Y. Shen, F. Lu, X. Cao, and H. Foroosh, "Video completion for perspective camera under constrained motion," in Proc. IEEE Conf. Pattern Recognit., pp. 63–66, 2006.