MOTION-BASED FEATURE CLUSTERING FOR ARTICULATED BODY TRACKING

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Abstract: The recovery of three dimensional structures from moving elements is one of the main abilities of the human perception system. It is mainly based on particularities of how we interpret moving features, especially on the enforcement of geometrical grouping and definition of relation between features. In this paper we evaluate how the human abilities of motion based feature clustering can be transferred to an algorithmic approach to determine the structure of a rigid or articulated body in an image sequence. It shows how to group sparse 3D motion features to structural clusters, describing the rigid elements of articulated body structures. The location and motion properties of sparse feature point clouds have been analyzed and it is shown that moving features can be clustered by their local and temporal properties without any additional image information. The assembly of these structural groups could allow the detection of a human body in an image as well as its pose estimation. So, such a clustering can establish a basis for a markerless reconstruction of articulated body structures as well as for human motion recognition by moving features.

1 INTRODUCTION

One of the main abilities of the human perception system is the interpretation of structure from motion. It is possible for us to estimate the form and the underlying body-structure of any object by only few moving elements like lines and points. Additionally, this ability is mostly independent from any environmental influences like e.g. a moving background, but also from the visual representation of the object itself as e.g. its size, colour or surface appearance.

This ability of motion perception is mainly based on particularities of how we perceive and interpret moving features, as has been shown in the experiments with moving light displays of Johansson (Johansson, 1973). The human perception usually forces a geometrical grouping and definition of relation between features. This can be based on spatial relations who are partly defined and summarized under the gestalt-principles, but also on the analysis of motion properties. The alignment and grouping of features allows the reconstruction of complex structures and their recognition even under not-optimal circumstances and with incomplete visual information.

In this paper we present three different feature clustering methods for 3D space and evaluate them with respect to their applicability for articulated body tracking. It is assumed, that every motion, and so also the motion of a human body in an image will result in some moving feature points. The motion of these feature points can allow determining the structure of the underlying rigid or articulated body. One main step towards such an application comprised the correct clustering of the moving features in order to detected rigid moving elements in the image. The presented approaches will show how to group motion features to structural clusters, describing the rigid elements of articulated body structures.

For the practical realization, we captured several image sequences with human motion. A motion based feature tracking method is applied to extract the moving features and to reconstruct their 3D positions. The 3D positions and motion properties of the resulting feature points are analysed in order to find structural clusters. These structural clusters describe feature sets with position and motion properties, characteristically for moving rigid structures, so that these clusters can be considered as

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candidates for the determination and tracking of underlying rigid body elements.

The assembly of these structural clusters could allow the detection of a human body in an image as well as its pose estimation and, considering a longer observation period, even motion recognition. So such a clustering can establish a basis for a markerless reconstruction of articulated body structures as well as for human motion recognition by moving features.

2 STATE OF THE ART

Automatic detection and tracking of people in different contexts has become a more and more relevant area in computer vision, especially in the context of motion analysis and recognition. The growing importance of this field is shown by the increasing number of surveys dealing with this subject (Moeslund, 2001 and 2006; Aggarval, 1999).

Feature-based human motion detection and analysis in this context is mainly based on marker tracking as presented by Cedras et al. or Holstein et al. (Cedras, 1994; Holstein, 2002), because predefined marker positions usually allow direct reconstruction of the underlying skeleton as shown by Silaghi et al. (Silaghi, 1998). A first approach for an application of markerless feature-based techniques in the context of human motion recognition is described by Song et al. (Song, 1999 and 2003). Here the motion of image features is used to detect human motion in an image sequence and to distinguish it from other moving elements, but the overall motion is not analysed

The second thematic focused in the here presented approach, the computation of feature grouping based on motion primitives, has been first described by Ullman (Ullman, 1983) and later by Aggarval et al. (Aggarval, 1994). Here, the applications range from basic computational studies of about interpretation of structure and motion up to optical flow based image segmentation (Nicolescu, 2002). We can see that, especially in the area of optical flow segmentation most techniques are designed for dense motion fields and so would probably not work for sparse feature maps with small structures, overlapping and twists, as they occur in articulated body tracking.

But the perception of moving structures based on the interpretation of motion is also still an open problem in neuroscience (Giese, 2003).

3 THEORETICAL APPROACH

In order to group moving features to structural clusters, it is first necessary to find acceptable criteria, describing the location and motion properties of points on rigid elements. The selection of clustering criteria is mainly based on three different approaches. The first two criteria are based on human interpretation of perception of rigid objects from 2-D motion presented e.g. by Ullman (Ullman, 1983): The first one is the velocity-based interpretation, where it is assumed that features that move in the same direction belong to one object. The second is the location-based interpretation, which means, that features that lay close together have a higher probability to belong to one object than features that are far away from each other.

In the here presented approach these criteria are extended to the three dimensional space. The transfer of the location- and velocity-based criterion from 2D to 3D is straight forward. And additionally for 3D space, a third, distance-variation-based criterion can be added. Assumed, that the features are fixed on the underlying element and do not change their 3D position relative to each other, they will also preserve the distance to all features that are lying on the same element. So, features whose distance relative to each other does not change over time are also probably suitable candidates to determine a rigid object.

Assuming features are situated on one rigid element, they will probably follow one or more of follow criteria:

Location Criterion. Two feature points, *a* and *b,* are rather located on the same rigid element if their 3D mean distance *d(a, b)* over *n* frames, shown in equation 1, is small:

$$d(a,b) = \frac{1}{n}\sum_{i=j}^{j+n}\sqrt{\left(a(i)_{(x,y,z)} - b(i)_{(x.y,z)}\right)^2} \qquad (1)$$

Velocity Criterion. If two feature points, *a* and *b*, have the same or a similar motion vector *v(a)* at the same time *i,* as described in equation 2, they are also likely to be located on the same rigid element:

$$v(a(i)) = \frac{1}{n}\sum_{i=j}^{j+n} d(a(i), a(i+1)\,) \qquad (2)$$

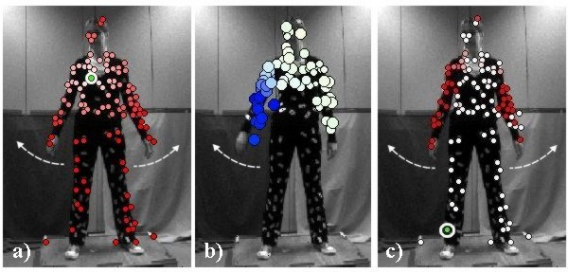


Figure 1: Visual representation of a) location-based, b) velocity-based and c) distance-variation-based cluster criterion.

Distance Criterion. If two feature points, *a* and *b*, do not change their distance *d(a, b)* to each other over time, as defined in equation 3, they are also likely to be located on the same rigid element:

$$d_{var(a,b)} = \frac{1}{n}\sum_{i=j}^{j+n} d\big(a(i), b(i)\big) - d\big(a(i+1), b(i+1)\big) \quad (3)$$

A visual representation of these criteria is presented in Figure 1. Here the three different distance measurements are applied to one, marked feature point. The distance is shown by the brightness of the related feature points. In Figure 1 b) the motion vector intensity is additionally displayed by the size of the feature point. Depending on the distance criterion, different feature regions are highlighted. Whereas the location-based distance in Figure 1a) is comprehensible, we can see that the distance measurement for the velocity- (Figure 1b) and distance-variation-based measurement (Figure 1c) shows a more structural result, where the highlighted regions mainly belong to currently rigid parts.

4 MOTION-BASED CLUSTERING

For the tracking and clustering of feature points the here presented approach proceeds as follows: For the detection and tracking of motion features, we used a motion based feature tracking approach described in (Koehler, 2008), which is mainly based on the pyramidal implementation of the KLT feature tracking method described in (Bouget, 2002), following the 'good features to track' method of Shi and Tomasi (Shi, 1994) and applied this to a set of stereo images. Then, the 3D position of the feature points is reconstructed and the result is a sparse 3D cloud of feature points, which are tracked over time. So it is also possible to apply time-based criteria e.g. the velocity and relative distance over time etc. The clustering is done for every single frame without the integration of precedent clustering results. So every frame is treated separately.

The criteria mentioned above, mean position, velocity and distance variance, are calculated for every 3D feature point. Then it is measured how much these features criteria *f*, e.g. the mean position, velocity or distance deviate from one feature point to the others. The deviation is computed as the Euclidean distance between pairs of feature primitives f_a and f_b described in equation 4.

$$d(f_a, f_b) = \sqrt{(f_a - f_b)^2} \quad (4)$$

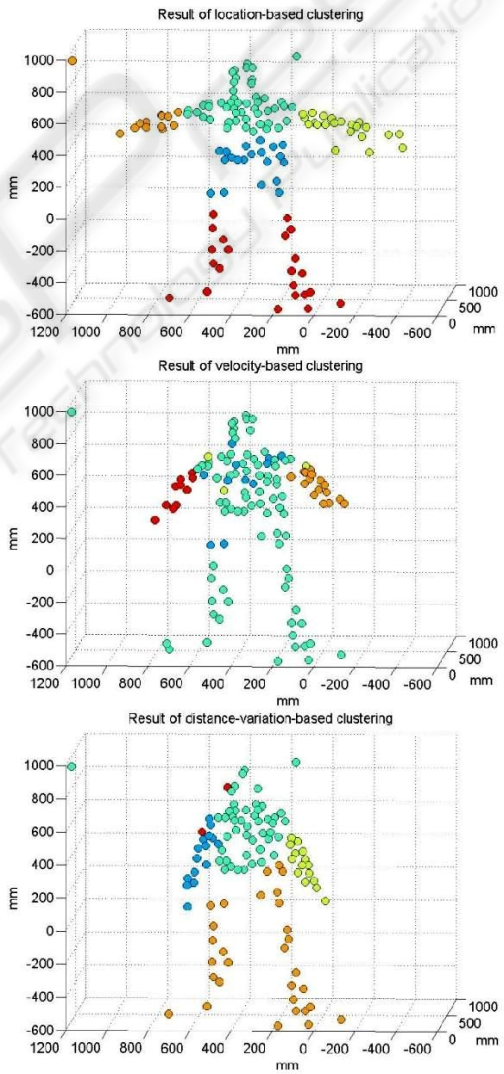


Figure 2: Clustering results for a) location-, b) velocity- and c) distance-variation-based cluster criterion.

Then, the clustering is done by arranging the resulting deviations $d(f_a,f_b)$ in a hierarchical cluster tree by preserving the minimum sum of squares of the distances between all cluster elements c_i in the cluster C and its centre point $\bar{c}$ (see equ. 5).

$$\bar{c} = \frac{1}{n}\sum_{i=1}^{n} c_i \qquad (5)$$

A fixed number of clusters are constructed from the resulting cluster tree by combining them with respect to the minimum distance criterion, whereas the linkage distance between two clusters C_a and C_b with the number of elements n_{Ca} and n_{Cb} and the centre points $\bar{c}_a$ and $\bar{c}_b$ is defined in equation 6 as:

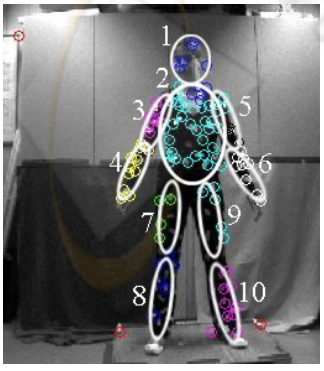
$$d_{link}(C_a, C_b) = n_{C_a} n_{C_b} \frac{d(\bar{c}_a, \bar{c}_b)}{(n_{C_a} + n_{C_b})} \qquad (6)$$

Examples for the results of the different criteria can be seen in Figure 2.

5 RESULTS

The approach has been tested on 12 stereo videos captured by a BumbleBee stereo camera with 20 fps and a resolution of 640x480px with 12 motion variations with duration from 5 - 20 sec. To get ground truth for the requested clustering, we labelled the features of 200 images by hand, defining 10 clusters representing the significant rigid parts of the human body as shown in Figure 3.

To evaluate the performance, the clustering correctness for the described criteria, local distance and velocity as well as distance variation has been analyzed. The mean results of the true-positive, false-positive, false-negative and true negative rate for the different criteria are shown in Figure 4.



1. head
2. body
3. upper right arm
4. lower right arm
5. upper left arm
6. lower left arm
7. upper right leg
8. lower right leg
9. upper left leg
10. lower left leg

Figure 3: Ground truth for the evaluation of clustering and corresponding labelling of body segments.

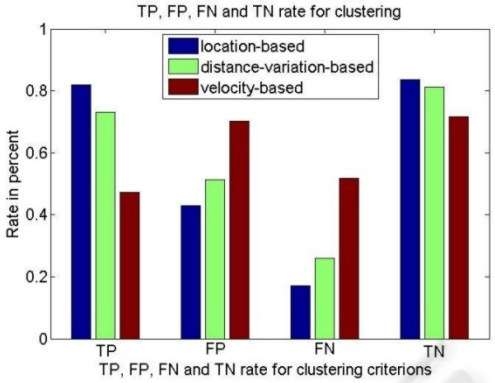


Figure 4: Overall true-positive, false-positive, false-negative and true negative rate for location-based, velocity-based and distance variation based clustering.

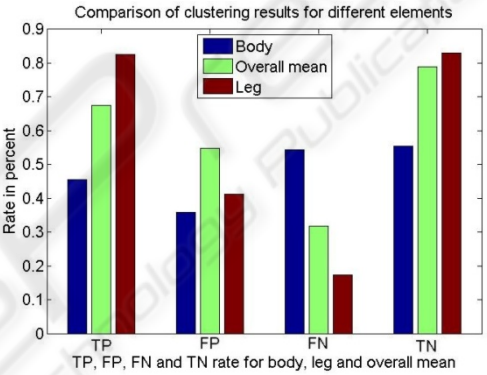


Figure 5: True-positive, false-positive, false-negative and true negative rate for different anatomical groups of clusters.

There is usually a high true-positive rate for the location-based as well as for the distance-variation-based clustering. Their mean true-positive rate over all body segments is 82.00 % for the location-based clustering and 81.37% much higher than the rate of the velocity based clustering which lies at 47.34%. Concerning the specificity of the clustering, the proportion of false-positive matches is very high. Here the tendency of the true positive rate repeats with a much better result of 42.87% and 51.40% for location-based and distance-variation-based clustering than for velocity-based clustering (70.23%). The results for the false-negative rates are in the best case for location based clustering at 17.20% (26.03% and 51.87% for distance-variation and velocity-based clustering). So we can see a tendency for under rather than for over segmentation.

It is also important to remark the qualitative differences of clustering correctness between the different body segments. As can be seen in Figure 5,

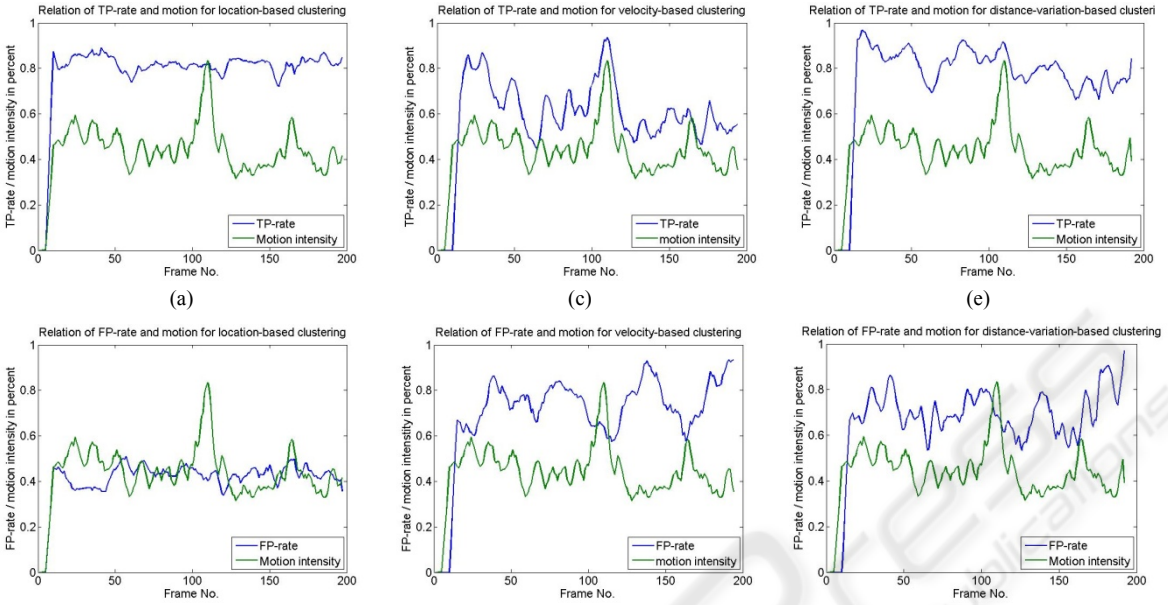


Figure 6: Relation of true-positive rate and motion intensity and false-positive rate and motion intensity for position based clustering, Figure a) and b), velocity based clustering, Figure c) and d) and distance variation based clustering, Figure e) and f). Especially for velocity based clustering, Figure c) and d), high motion intensity leads to an increase of the true-positive rate and to a decrease of the false positive rate.

the mean true-positive rates for the upper and lower extremities are usually over 80% whereas the head and especially the torso tend to show a significantly lower mean true-positive rate. This is mainly caused by the fact that the torso is often segmented into two or three different clusters. It usually divides into an upper and a lower part, defining a pelvis segment and a chest segment. The chest segment is, depending on the actual motion sometimes also divided into a left and right part, mainly because the motion of the chest muscles usually support the motion of the upper arm, so that they form two independent segments. This peculiarity has not been taken into account for the here presented evaluation but should be respected in the future, especially when it comes to the definition of an underlying motion model.

Considering that only motion based criteria are used, it is easy to see that the evaluation will fail sometimes, e.g. if the person stands still, just because there would not be any meaningful input data when nothing moves. So, it is important to know under which conditions a clustering would conform to appropriate motion requirements.

So is the outstanding position of velocity-based clustering in the overall correctness evaluation (Figure 4) mainly based on the fact that it depends on a certain amount of motion in the image. So, the more features are moving in the image, the more precise this method works. On the other hand side, when there are only few moving features in the image, this method usually fails. This close relation between motion and the amount of true-positive and true-negative features is display in Figure 6c) and d). It is clear to see, that high motion intensity also leads to an increase of the true-positive rate and to a decrease of the false positive rate and vice versa, whereas e.g. the location-based clustering is not affected by the motion intensity (Figure 6a) and b)). Concerning the reliability of clustering, we can see that frames with a high proportion of moving feature usually also have a equal or even higher specificity of clustering (Figure 6, all) than those with only few moving features. So, moving elements in an image usually improve the overall clustering results. This is comprehensible, considering the fact that especially the distance-variation-based and even more the velocity-based clustering depend on temporal interpretation of the data.

For a further combination of the different criteria, it can be useful to take advantage of this characteristic by integrating the motion intensity as an additional factor. This allows to concentrate on the results of location-based clustering, when there

is only low motion intensity and to integrate distance-variation- and velocity-based clustering when the motion intensity increases as well as to estimate the reliability of the actual result, which could be useful for subsequent processing.

6 CONCLUSIONS

We presented three different feature clustering methods and evaluated them with respect to their applicability for articulated body tracking. We showed that moving features can be clustered just by their local and temporal properties without any additional image information and so, that the feature motion can allow determining the structure of the underlying e.g. rigid or articulated body. The results showed that an acceptable correctness can be archived by the presented cluster techniques, according to various circumstances. The here presented evaluation can serve as a basis to combine the strong points of every cluster criterion. This becomes important with regarding further development up to a consistent cluster tracking for longer motion sequences, but also regarding e.g. the connection of the feature clusters in order to define an underlying articulated motion model.

So, the here presented alignment and grouping of features provides a basis for the reconstruction of complex structures and their recognition.

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REFERENCES

Aggarwal, J.K., Cai, Q., 1999. Human Motion Analysis: A Review. In *Computer Vision and Image Understanding*, Vol. 73, No. 3, pp. 428-440.

Aggarwal, J.K., Cai, Q., Liao, W., Sabata, B., 1994. Articulated and elastic non-rigid motion: A review. In *Proc. IEEE Workshop on Motion of Non-Rigid and Articulated Objects*, pp 2-14.

Bouguet, J.-Y., 2002. Pyramidal implementation of the Lucas Kanade feature tracker, description of the algorithm. *Technical report*, Intel Corporation.

Cedras, C., Shah, M. 1994. A Survey of Motion Analysis from Moving Light Displays. In *IEEE Conf. on Computer Vision and Pattern Recognition*, pp. 214-221.

Corazza, S., Mündermann, L., Andriacchi, T., 2007. A framework for the functional identification of joint centers using markerless motion capture, Validation For The Hip Joint. In *Journal of Biomechanics*

Giese, M. A., Poggio, T., 2003. Neural mechanisms for the recognition of biological movements and action. In *Nature Reviews Neuroscience*, Vol. 4, pp. 179-192.

Holstein, H., Li, B., 2002. Low Density Feature Point Matching for Articulated Pose Identification. In *British Machine Vision Conference 2002*, pp 678 - 687

Johansson, G., 1973. Visual perception of biological motion and a model for its analysis. In *Perception & Psychophysics*, Vol. 14, No. 2, pp. 201 - 211.

Koehler, H., Pruzinec, M., Feldmann, T., Woerner, A., 2008. Automatic Human Model Parametrization From 3D Marker Data For Motion Recognition. In *Int. Conf. in Central Europe on Computer Graphics, Visualization and Computer Vision*, Pilsen, 2008

Moeslund, T.B., Granum, E., 2001. A survey of computer vision-based human motion capture. In *Computer Vision and Image Understanding*, Vol. 81, No. 3, pp. 231-268.

Moeslund, T.B., Hilton. A., Krüger, V., 2006. A survey of advances in vision-based human motion capture and analysis. In *Computer Vision and Image Understanding*, Vol. 104 , No. 2, pp. 90 – 126.

Nicolescu, M., Medioni, G., 2002. Perceptual Grouping from Motion Cues Using Tensor Voting in 4-D. In *European Conf. on Computer Vision*, LNCS 2352, pp. 423 - 437

Shi, J., Tomasi, C., 1994. Good Features to Track. In *IEEE Conf. on Computer Vision and Pattern Recognition*, pp. 593 - 600.

Silaghi, M.-C., Plänkers, R., Boulic, R., Fua, P., Thalmann, D., 1998. Local and Global Skeleton Fitting Techniques for Optical Motion Capture. In *Proc. of the International Workshop on Modelling and Motion Capture Techniques for Virtual Environments*, LNCS 1537, pp. 26-40.

Song, Y., Goncalves, L., Di Bernardo, E., Perona,P., 1999. Monocular Perception of Biological Motion - Detection and Labeling. In *Proc. of the Int. Conf. on Computer Vision*, Vol. 2, pp. 805-812.

Song, Y., Goncalves, L., Perona, P., 2003. Unsupervised Learning of Human Motion. In *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 25 , No. 7, pp. 814-827

Tomasi, C., and Kanade, T., 1991. Detection and tracking of point features. *Technical Report*, School of Computer Science, Carnegie Mellon University

Ullman, S., 1983. Computational Studies in the Interpretation of Structure and Motion: Summary and Extension. In *Human and Machine Vision*, Academic Press