Comparing Improved Versions of 'K-Means' and 'Subtractive' Clustering in a Tracking Application

Marta Marrón Romera, Miguel Angel Sotelo Vázquez, and Juan Carlos García García

Electronics Department, University of Alcala,
Edificio Politécnico, Campus Universitario Alcalá de Henares, 28871, Madrid, Spain
{marta,sotelo,jcarlos}@depeca.uah.es

Abstract. A partitional and a fuzzy clustering algorithm are compared in this paper in terms of accuracy, robustness and efficiency. 3D position data extracted from a stereo-vision system have to be clustered to use them in a tracking application in which a particle filter is the kernel of the estimation task. 'K-Means' and 'Subtractive' algorithms have been modified and enriched with a validation process in order improve its functionality in the tracking system. Comparisons and conclusions of the clustering results both in a stand-alone process and in the proposed tracking task are shown in the paper.

Keywords: clustering, probabilistic-deterministic, particle-filters, tracking.

1 Introduction

Clustering algorithms are used in a large amount of applications ([1], [2], [3]). In artificial vision, these processes are particularly useful as compress visual data generating classes that contain more accurate and robust environmental information.

In the application developed by the authors in [4], information about the 3D position of a variable number of objects in an indoor environment is obtained from a stereo-vision system and used as measurement vector of a probabilistic estimation process, in a multi-obstacle detection and tracking process. This information is clustered in 2D before using it in the probabilistic tracker, as it is explained in [4].

It has been proven ([5]) that an association algorithm is needed in order to make robust the multi-tracking process. Most of the association solutions are based on the Probabilistic Data Association (PDA) theory [6], such as the Joint Probabilistic Particle Filter (JPDAF) like in [7], but the computational load of these techniques is generally a problem for the real time execution of the tracking algorithms. On the other hand, some of the solutions presented by other authors ([8]) lack of robustness if the measurements used in the estimation process are not wisely preprocessed. The use of a clustering process solves the association problems.

Fig. 1 includes a flowchart describing the global tracking application. In the same figure, an image showing the 3D position data extracted from the objects to track in a real experiment is also included, as white dots.

It has to be remarked that, though 3D position information of the objects to be tracked is available, the height coordinate of these data is not useful in the clustering, and thus, the position measurements are cluster in a 2D space.

R. Moreno-Díaz et al. (Eds.): EUROCAST 2007, LNCS 4739, pp. 717–724, 2007.

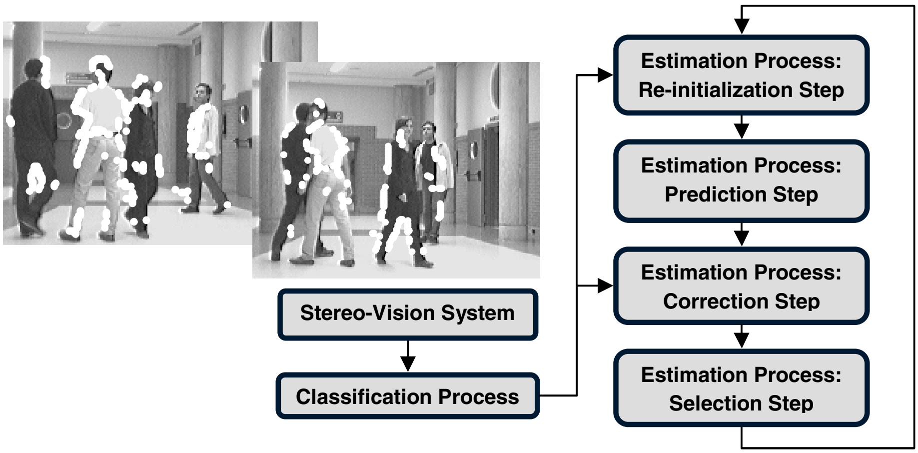

Fig. 1. Functional description of the multimodal estimation tracker, and the clustering process implication in it. A frame extracted from a real experiment is also included. In the image the position data points to be clustered are plotted in white.

On the other hand, as it can be notice in Fig. 1, position measurements extracted by the stereo-vision system are not equally distributed among all objects in the environment, and hence, the tracking algorithm, and what is of interest in this paper, clustering proposals should be able to manage clusters with very different likelihood.

In this paper, two different clustering algorithms are tested and compared in order to find the most adequate solution for the tracking task exposed. The contributions of the clustering proposal to the multi-tracking process are also shown in the paper.

2 Clustering Algorithms

As mentioned two different clustering algorithms are compared in their application to the objective pursuit. They are described in the following paragraphs:

- *Modified 'K-Means':* The deterministic solution presented by MacQueen in [9], and afterwards improved ([10]), is modified to classify a variable number of clusters. A flowchart of this clustering proposal is presented in Fig. 2, in which the functionality included to achieve an adaptive behavior of the algorithm to the number of clusters generated by the algorithm is marked with a dashed line. On the other hand, in order to improve the algorithm speed in its recursive performance ([11]), the 'K-Means' segmentation process starts looking for clusters centroides near the predicted values that are calculated with the clustering results in the previous execution of the algorithm. This other improvement is also shown in dashed line in Fig. 2.
- *Modified 'Subtractive':* This algorithm is a fuzzy solution for the clustering task based on the Mountain algorithm [12], and presented afterwards in [13]. The 'Subtractive' algorithm is unlinked, and therefore a process to obtain the each cluster centroide and the members has to be included in the standard algorithm if

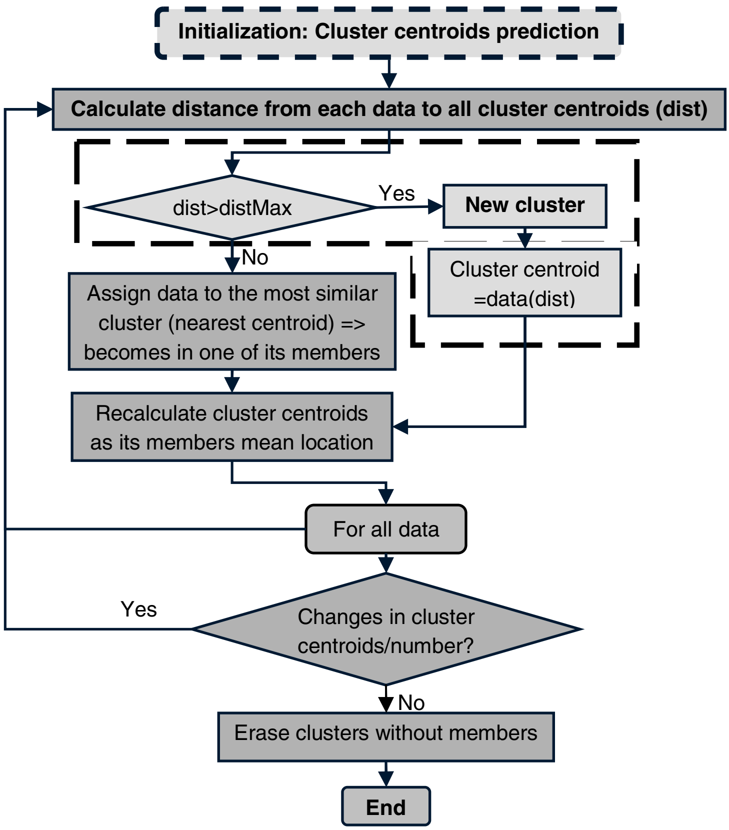

Fig. 2. Flowchart of the modified 'K-Means' proposed by the authors. Dashed lines remark the main improvements included in the standard version of the algorithm.

needed, as it is in the present application. This improved functionality is shown with dashed lines in Fig. 3. Moreover, the probability of each cluster members is reset in order to decrease the cluster duplication error rate of the standard fuzzy classifier. This process is also included in Fig. 3 with dashed lines.

All the modifications described increase the efficiency and accuracy of the basic classifiers. To improve their robustness, a validation process is also added to both clustering algorithms. This procedure is useful when noisy measurements or outliers produce a cluster creation or deletion erroneously. In these situations none of the modified algorithms shown in previous figures behave robustly. The validation process is based in two parameters:

- *Distance between the estimated and the resulting cluster centroide.* The clusters centroide estimation process in the modified 'K-Means' is also developed for the 'Subtractive' version of Fig. 3. Estimated centroides are then compared within two consecutive iterations, to obtain a confidence value for clusters validation.

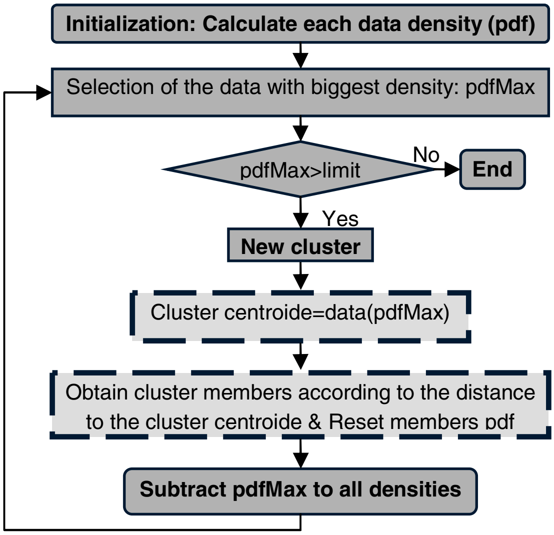

Fig. 3. Flowchart of the modified 'Subtractive' algorithm proposed by the authors. Dashed lines remark the main improvements included in the standard version of the algorithm.

- *Cluster likelihood.* The clusters probability information inherent in 'Subtractive' algorithm is also calculated in 'K-Means', as a function of the data agglomeration in each cluster. This likelihood value is also used as a validation or confidence parameter in the cluster validation process.

In the following sections the results obtained with the clustering proposals described are deeply commented.

3 Comparison

In order to extract comparative conclusions about the accuracy, robustness and efficiency of the clustering methods presented, they have been run with different data sets containing 2D position measurements obtained from the objects in the environment during the tracking task.

The objective in all situations is that a cluster is created for each object in the scene by the algorithms if some data points related to it are present in the clustered data set. The main conclusions extracted from the global set of experiments (2931 frames of 3 situations of different complexity) are the following:

- In general 'K-Means' shows higher reliability than 'Subtractive', with a mean error rate of 3.9% against 6.7%.
- High accuracy is obtained in the whole testing process, since less than a 1% of errors is due to shifts if 'K-Means' is used, and 1.6% if it is 'Subtractive'.
- The most recurrent error (half of the global error rate with both algorithms) appears when an object is poorly measured and only a few data points related to it are included in the set. This type of error is generally called a missing error.

- The generation of a duplicated class related to the same object is a typical error generated by 'Subtractive' (1.2% error rate against less than 1% in 'K-Means'). Nevertheless this error rate is doubled if the reset process included as an improvement in the 'Subtractive' algorithm is not used.
- The validation process proposed rejects almost the 90% of noisy measurements when included in any of the clustering algorithms. In any case, 'Subtractive' clustering behaves better with noisy measurements than 'K-Means' as almost 50% of the global error rate when using 'K-Means' is due to noise.
- 'K-Means' is less time consuming than 'Subtractive' (a mean execution time of 1.5ms for 'K-Means' versus 17ms for 'Subtractive'[1]). The execution time of 'K-Means' is decreased almost in a 50% if using the centroide estimation process.

Table 1 shows the main errors generated by both clustering proposals in a complex experiment of 1054 frames, in which situations of until 6 static and dynamic classes are included. The results displayed in the table validate the comments exposed in previous paragraphs and confirm the better behavior of the clustering proposal based on the standard 'K-Means'.

Table 1. Rate of different types of errors obtained with the proposed versions of 'K-Means' and 'Subtractive' algorithms in a 1054 frames experiment of none until 6 classes

	K-Means (% frames with error)	**Subtract (% frames with error)**
Missing	10.9	19.3
Duplicated	6.1	16.2
Shift	0	9.7
2 as 1	3.9	2.3
Total	**20.9**	**47.4**

Fig. 4 shows the results of two sequential iterations of the clustering proposals in the complex experiment mentioned. Numbers at the top and at the bottom of the images indicate the number of clusters generated by 'K-Means' and 'Subtractive', respectively. Regular rectangles display the clusters generated by 'K-Means', and dashed the ones generated with 'Subtractive'. In the image of the right, the shift error generated by 'Subtractive' clustering can be observed in person tacked with number 3. In the left image, a missing error generated by 'Subtractive' with person number 4 that is partially occluded by person number 2, is shown. Results generated by 'K-Means' clustering are right in both cases.

The error rate is, in any case, too high to use the output of the clustering process as output of the multi-tracking process. The difference in the likelihood of the measurements sensed by the stereo-vision system for each object in the environment cannot be properly handled by the clustering proposals. The use of a probabilistic estimator that reinforces the probability of poorly sensed objects is therefore justified.

---

[1] The algorithms are run in an Intel Dual Core processor at 1.8GHz with 1Gbyte RAM.

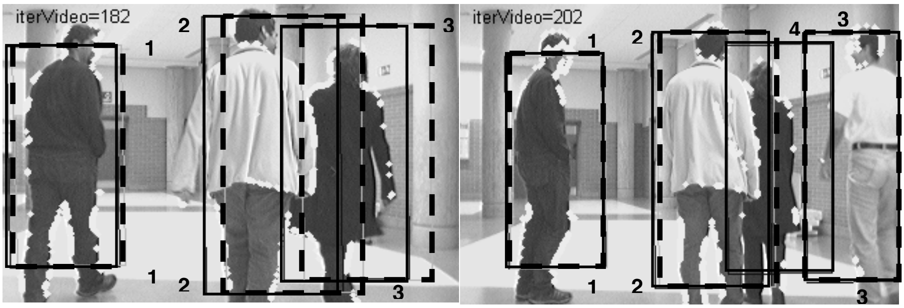

Fig. 4. Two sequential images extracted from a complex experiment. Clustering results are shown with regular rectangles for the 'K-Means' proposal and dashed for the 'Subtractive' one.

4 Application of the Clustering Algorithms to the Tracking Process

As mentioned in section 1, the clustering algorithms developed were designed to be used in a multi-tracking application ([4]), in order to increase the tracker robustness.

A particle filter (PF) is used as position estimator, and the algorithm is extended and the clustering process is used as association process in order to achieve the desired functionality and efficiency of the multi-tracker. The final algorithm is called 'Extended Particle Filter with Clustering Process' (XPFCP).

The functionality of the clustering algorithms in the tracking process is analyzed in detail in [4]. The general idea is to use the process in two different steps of the multimodal estimator (see Fig. 1) as follows:

- *At the re-initialization step*, position information compressed within the clusters is used to create new hypotheses in the multimodal estimator. The clustering process is thus used to adapt the tracker functionality to situations with a variable number of objects.
- *At the correction step*, the cluster probability is used to reinforce or weaken each object position estimation hypothesis. This procedure increases the robustness of the global tracking task.

Both algorithms have been used within the probabilistic tracker mentioned, to test which one is the best solution to increase the multimodal estimator robustness.

Table 2 summarizes the results obtaining when comparing both clustering proposals in the XPFCP designed, in the same 1054 frames experiment used to extract results in Table 1. As it can be notice in the table, the solution based on 'K-Means' has better performance than the one based on 'Subtractive'.

In a more general set of tests (2931 frames of 3 situations of different complexity) the results are similar to those shown in Table 2:

- The mean error rate is 1.8% if using 'K-Means' and 3.7% if using 'Subtractive' in the multi-tracking algorithm. Moreover, only missing errors appear if using the 'K-Means' algorithm, while the 'Subtractive' proposal shows also duplicating errors.
- The mean execution time of the multimodal tracker is 19.1ms when using 'K-Means', almost four times lower than if 'Subtractive' is used (73.3ms). The reason

for this difference is that the execution time of the estimation process without clustering is comparable to the one of the stand alone version of 'Subtractive' (a mean value of 17.8ms).

- Outliers do not appear in the tracker results, so the problem of noise has been erased from the tracking application, thanks to the clustering process.

Table 2. Rate of different types of errors obtained with the XPFCP proposed in a 1054 frames tracking experiment of none until 6 classes

	K-Means (% frames with error)	Subtract (% frames with error)
Missing	12.9	16.4
Duplicated	0	4.7
Total	**12.9**	**21.1**

All exposed results recommend the use of 'K-Means' in the multi-tracking process. An example of the results achieved with the XPFCP is shown in Fig. 5, where the modified 'K-Means' is used as association process in the multi-object tracker. Tracked objects are displayed with rectangles in the images. This figure proofs the correct functionality of the global proposed tracker also in crowd situations where multiple objects cross and are partially occluded during various iterations.

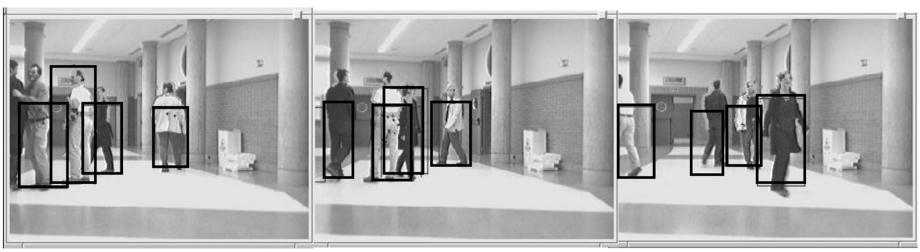

Fig. 5. Three frames in a real tracking sequence showing results generated by the XPFCP in the tracking process. Clusters are plotted with rectangles.

5 Conclusions

In this paper two new clustering proposals based on the standards 'K-Means' and 'Subtractive', are presented. The improved algorithms are thought to be applied in the multi-object tracking system described by the authors in [4], called XPFCP. The clustering process is used as association algorithm in the multimodal estimator. On the other hand, the use of clustered measurements increases the tracker robustness.

The two clustering proposals performance is compared and some interesting conclusions are extracted:

- The proposal based on 'K-Means' shows higher reliability than the one based on 'Subtractive'.

- 'Subtractive' behaves better with noisy measurements than 'K-Means', but the validation process included in both clustering proposals solves successfully the robustness problems generated by outliers.
- The execution time of 'Subtractive' is almost 10 times bigger than the 'K-Means' one, and comparable to the multimodal estimator one.

All these conclusions recommend the use of the modified 'K-Means' in the XPFCP, and the success of the resultant multi-tracking algorithm is also demonstrated in the paper.

Acknowledgments. This work has been financed by the Spanish administration (CICYT: DPI2005-07980-C03-02).

References

1. Jain, A.K., Murty, M.N., Flynn, P.J.: Data clustering: a review. ACM Computing Surveys 31(nº 3), 264–323 (1999)
2. Berkhin, P.: Survey of clustering data mining techniques. Technical Report (2002)
3. Everitt, B., Landau, S., Leese, M.: Cluster analysis. Edward Arnold Publishers, 4th Edition, London, ISBN: 0-340-76119-9 (2001)
4. Marrón, M., Sotelo, M.A., García, J.C., Fernández, D., Pizarro, D.: XPFCP: An extended particle filter for tracking multiple and dynamic objects in complex environments. In: Proceedings of the 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS05), Edmonton, pp. 234–239 (2005), ISBN: 0-7803-9252-3
5. Isard, M., Blake, C.A.: Conditional density propagation for visual tracking. International Journal of Computer Vision 29(nº1), 5–28 (1998)
6. Bar-Shalom, Y., Fortmann, T.: Tracking and data association. Mathematics in Science and Engineering, vol. 182. Academic Press, London (1988)
7. Schulz, D., Burgard, W., Fox, D., Cremers, A.B.: People tracking with mobile robots using sample-based joint probabilistic data association filters. International Journal of Robotics Research 22 (nº 2), 99–116 (2003)
8. Koller-Meier, E.B., Ade, F.: Tracking multiple objects using a condensation algorithm. Journal of Robotics and Autonomous Systems 34, 93–105 (2001)
9. MacQueen, J.B.: Some methods for classification and analysis of multivariate observations. In: Proceedings of Fifth Berkeley Symposium on Mathematical Statistics and Probability, Berkeley, vol. 1, pp. 281–297 (1967)
10. Pelleg, D., Moore, A.: X-means: Extending k-means with efficient estimation of the number of clusters. In: Proceedings of the Seventeenth International Conference on Machine Learning (ICML00), San Francisco, pp. 727–734 (2000) (ISBN: 1-55860-707-2)
11. Weiss, Y.: Belief propagation and revision in networks with loops. Technical Report 1616, Artificial Intelligence Laboratory, Massachusetts Institute of Technology (1997)
12. Yager, R.R., Filev, D.: Generation of fuzzy rules by mountain clustering. Journal of Intelligent and Fuzzy Systems 2(nº 3), 209–219 (1994)
13. Chiu, S.L.: Fuzzy model identification based on cluster estimation. Journal of Intelligent & Fuzzy Systems 2(nº 3), 267–278 (1994)