TP1

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Work done individually

For doing this lab I tried to implement the “**Adaptive background mixture models for real-time tracking**” paper. I had also taken help from “**Parameter Analysis for Mixture of Gaussians Model**” and “**Practical Mixtures of Gaussians with Brightness Monitoring**” for the parameters.

I have also used ideas and sentences from above papers to answer below questions. I also thank Pierre-Luc St-Charles for clearing my doubts patiently and guiding me.

**Discutez brièvement le problème adressé dans ce TP ainsi que le type d'approche de segmentation étudié (avantages, inconvénients, …).**

There is a need to classify background and foreground for surveillance systems. So in this lab I am trying to segment the background and foreground from a video.The Gaussian distributions of the adaptive mixture model are evaluated to determine which are most likely to result from a background process*.* For doing this I tried to implement the “**Adaptive background mixture models for real-time tracking**” paper. I had also taken help from “**Parameter Analysis for Mixture of Gaussians Model**” and “**Practical Mixtures of Gaussians with Brightness Monitoring**” for the parameters.

So in this implementation each pixel is modelled as a mixture of Gaussians and using an on-line approximation to update the model. Our approach is adaptive and is better than non-adaptive methods where there is need for manual initialization. Though initialization is done in this method, we are updating the parameters according to previous data .We can’t say it is completely independent of initialization data, but better than the non-adaptive methods. The usage of multiple Gaussians to model a pixel makes the result better as many changes can be accounted like lighting changes, noise.

Advantages:

* Robust against movement that are part of background like the branches of tree i.e. its bimodality
* Robust against weather changes
* This method adapts to deal robustly with lighting changes, repetitive motions of scene elements, tracking through cluttered regions, slow-moving objects, and introducing or removing objects from the scene.
* It is a real-time approximate method which is stable and robust.

Disadvantages:

* It doesn’t work well with shadows.(by increasing the number of components can make it better, but we also have to take care of performance)
* Not adaptive to very fast light changes
* Can’t detect distinct objects if they overlap

**Présentez votre implémentation en discutant de vos choix de paramètres (nombre de**

**gaussiennes, taux d'apprentissage, proportion de l'arrière-plan, …) et leur impact sur la**

**qualité de la segmentation finale de la séquence 'video1.avi' disponible sur Moodle (une**

**image vaut mille mots...).**

The first parameter I would like to discuss is the number of component( Gaussians) per pixel. I have chosen 3 and anything above 3 will be useless as there is not much improvement in the result. I think 3 is sufficient as the background lighting is fairly constant i.e. there are no drastic lighting changes and I also simplified my image by taking the grey scale, so 3 components would be sufficient. The next parameter is ‘B’ which is the number of background components to consider. I had taken it equal to ‘K=3’ as my number of Gaussian components are fairly less. Next I had taken ‘alpha = 0.01 ‘ which is the learning rate. I had estimated it using the half-life formula from the paper ‘Practical Mixtures of Gaussians with Brightness Monitoring’. I had seen the results from the nearby learning rates and this learning rate had given nearly good output. I had taken initial standard deviation as ‘6’. I had also tried other values like ‘12’ which was suggested in ‘**Parameter Analysis for Mixture of Gaussians Model**’. Finally I had taken background threshold as ‘0.25 ’ , though in the paper other values in the range 0.4-0.5 were suggested , 0.25 gave better results, so I had used this value.

**Expliquez pourquoi l'utilisation d'une simple gaussienne est insuffisante pour la**

**modélisation d'une scène extérieure typique.**

An outdoor environment has many changes like lighting changes, weather changes, background changes (new trees, new buildings), repetitive motions and top of that the noise. To deal with these many kinds a single Gaussian would be insufficient. The bimodality of an outdoor environment doesn’t allow us to model using a single Gaussian. Ridder et al.[1] modelled each pixel with a Kalman Filter which made their system more robust to lighting changes in the scene. While this method does have a pixel-wise automatic threshold, it still recovers slowly and does not handle bimodal backgrounds well. If each pixel resulted from a particular surface under particular lighting, a single Gaussian would be sufficient to model the pixel value while accounting for acquisition noise. In practice, multiple surfaces often appear in the view frustum of a particular pixel and the lighting conditions change. Thus, multiple, adaptive Gaussians are necessary. We use a mixture of adaptive Gaussians to approximate this process.

**Finalement, proposez une amélioration possible à cet algorithme de base qui pourrait,**

**selon vous, améliorer le résultat de la segmentation.**

As suggested in the paper by Grimson and Stauffer, the connected components algorithm will improve the segmentation result. The Mixture of Gaussians method described above allows us to identify foreground pixels in each new frame while updating the description of each pixel’s process. These labelled foreground pixels can then be segmented into regions by a two-pass, connected components algorithm [2]. This post processing step would give better segmentation result. Adding prediction to each Gaussian (e.g. the Kalman filter approach), may also lead to more robust tracking of lighting changes.

**References**

[1] Christof Ridder, Olaf Munkelt, and Harald Kirchner.

“Adaptive Background Estimation and Foreground Detection

using Kalman-Filtering,” *Proceedings of International*

*Conference on recent Advances in Mechatronics*,

ICRAM’95, UNESCO Chair on Mechatronics, 193-199,

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[2] B. K. P. Horn. *Robot Vision*, pp. 66-69, 299-333. The MIT

Press, 1986.