Objects Tracking in Catadioptric Images using Spherical Snake

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Abstract: The current work addresses the problem of 3D model tracking in the context of omnidirectional vision in order to object tracking. However, there is few articles dealing this problem in catadioptric vision. This paper is an attempt to describe a new approach of omnidirectional images (gray level) processing based on inverse stereographic projection in the half-sphere. We used the spherical model. For object tracking, The object tracking method used is snake, with optimization using the Greedy algorithm, by adapting its different operators. This method algorithm will respect the deformed geometry of omnidirectional images such as the *spherical neighbourhood*, the *spherical gradient* and reformulation of optimization algorithm on the spherical domain. This tracking method - that we call *spherical snake* - permit to know the change of the shape and the size of 2D object in different replacements in the spherical image.

1 INTRODUCTION

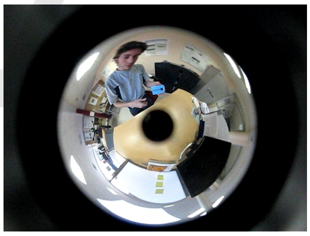
In the context of computer vision, we describes a method for processing, analysing, and understanding images. The visual tracking is an important task in computer vision applications such as video surveillance, Radar, mobile robotics. This paper define the tracking objects in a catadioptric images sequence.The first one is realise an adapted process in spherical images. The second is make possible non−rigid objects tracking.

According to (Baker and Nayar, 2001), every omnidirectional image taken using a camera with a single view point (SVP) can be modeled by a spherical image (illustrated in figure.1). This unified projection model was introduced in (Geyer and Daniilidis, 2001). In fact, the projection onto the sphere takes into account the non linear resolution conforming to the shape of the catadioptric mirror.
Basically the spherical coordinates of spherical point P are defined as the following equation:

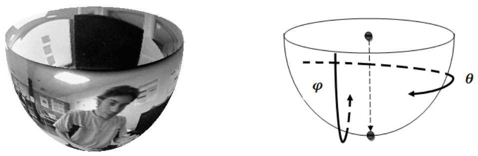
$$P = (\cos(\varphi)\sin(\theta), \sin(\varphi)\sin(\theta), \cos(\theta)) \quad (1)$$

The stereographic projection of P from the sphere to the catadioptric plane can be expressed on Cartesian coordinates::

$$(u, v) = (\frac{X}{1-Z}, \frac{Y}{1-Z}) \quad (2)$$



(a) Omnidirectional Image



(b) Spherical Image (c) Spherical coordinates
Figure 1: Omnidirectional spherical Image.

Using Equation. (1) and (2), we obtain the image point $P_i(x, y)$ expressed on spherical coordinates as Equation. (3):

$$(u, v) = (\cot\frac{\theta}{2}\cos(\varphi), \cot\frac{\theta}{2}\sin(\varphi)) \quad (3)$$

where θ is the latitude varying between 0 and π , and φ is the longitude varying between 0 and 2π. The localization of a point with spherical coordinates is defined by the two parameters (θ,φ). This paper is organized as follows. Firstly, a brief review of existing

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tracking methods for perspective and omnidirectional images sequence is given in Section 2. Secondly, in Section 3, active contour models will be introduced and traditional object tracking approaches based on snakes will be reviewed. The section 4 is dedicated to the adaptation the snake method for spherical images. Eventually, in section 5, some results on snake tracking in omnidirectional images sequences will be presented and commented.

2 RELATED WORKS

Object tracking in a complex environment needs a powerful algorithm. The motion of the object, with the changing illumination and the textured background, are stages to overcome.
In this paper, we solve the problem related to changing size of moving object by using the snake method. Many deterministic methods have been developed in the literature and can be roughly divided into tree groups: Tracking based on kernel, on points, or on contours and silhouette. Methods of the first group, such as the mean-shift tracker (Comaniciu et al., 2000) make the difference between a reference image and the correct image to detect the object. However, methods of the second group use tracking characteristic points of object. These include the SIFT tracker (Lowe, 2010) and the Kanade-Lucas-Tomasi(KLT) tracker (Lucas and Kanade, 1981). In last, methods based on contour use the energy minimization such us the Snake tracker (Kass et al., 1988). In addition, there are methods based on the probability estimation of the space prediction of the moving object to model its underlying dynamics. These include the Kalman filter and particle filters (Isard and Blacke, 1998). These methods have been successfully employed in various application domains. They cannot be directly applied to images acquired by catadioptric cameras.
In this context, a few methods have been developed in the literature. The visual trackers are able to properly follow a target through a video sequence taken with a catadioptric camera. Consequently the most adopted method is based on statistic calculator. But do not forget the Caron work in (Caron et al., 2012) whose consider a sensor which combines a camera and four mirrors for pose estimation, using an object model composed of lines. In (Mei et al., 2006), the author presents a homography-based approach for tracking multiple planar templates.
First, the adaptation of conventional particle filter to the catadioptric geometry was purposed in (Ikoma et al., 2008). This is done by adapting the window used to define the object appearance on the unitary sphere. Secondly, the authors in (Hurych et al., 2011) propose a new method to display tracking result from weighted particles obtained from the estimation process by SMC (Sequential Monte Carlo).
We chose the snake method for several reasons. This method contains in its algorithm operators will be adapted. The neighbourhood, the gradient image, the Gaussian filter... in the spherical space.

3 CLASSIC SNAKE FOR TRACKING

A considerable work has been done during the past decade in object tracking of non-rigid objects in the context of snake models. Snake, one of the active contour models, was introduced by Kass and al. in (Kass et al., 1988).
In our context (i.e. tracking), we used a Snake method based on energy minimization to detect the object contours.

On one first hand, we place around the object contour to detect an initial contour points manually if we find a difficulty to object detect. On the other hand, we use an automatic detection by background subtraction algorithm. This method is effective for this work in the first image sequence to detect the desired object. The snake tracker in the others images sequence.

3.1 Energies

The snake method defined by energies such as internal energy, external energy and context energy Equation. (4). The snake method defined by energies such as internal energy called E_{int}^{pi}, external energy E_{ext}^{pi}. Where $p_i = (x_i, y_i)$ and i represents the contour point index.

$$E_{Tot} = \sum_{i=1}^{N} (a * E_{int}^{pi} + \gamma * E_{ext}^{pi}) \quad (4)$$

The internal energy is defined by Equation. (5). This energy represent the curve continuity (first part) and convexity (second part). where α is the continuity coefficient, β is the convexity coefficient.

$$\begin{aligned} E_{int} = & \int_0^1 \frac{\alpha}{2}(s) \left\| V_i'(s) \right\|^2 ds \\ & + \int_0^1 \frac{\beta}{2}(s) \left\| V_i''(s) \right\|^2 ds \end{aligned} \quad (5)$$

We used the theorem of ”finite differences” to remedy the problem of approximated derivative into the difference Equation. (6) and (7).

$$|V_i(s)'|^2 = ||\frac{dv_i}{ds}||^2 \approx ||v_i - v_{i-1}||^2 = (x_i - x_{i-1})^2 + (y_i - y_{i-1})^2 \quad (6)$$

$$|V_i(s)''|^2 = ||\frac{d^2 v_i}{ds^2}||^2 \approx ||v_{i-1} - 2v_i + v_{i+1}||^2 = (x_{i-1} - 2x_i + x_{i+1})^2 + (y_{i-1} - 2y_i + y_{i+1})^2 \quad (7)$$

where $V_i(s) = (x_i(s), y_i(s))$ is the snake point in the contour s.

The continuity energy affects the contour radius in the contour points to be positioned in equal distance between them and depends on the curve intensity. when $\alpha = 0$ the curve has discontinuities. The second energy used for the internal energy is the curvature and highlights the curve convexity. This convexity becomes strong when $\beta = 0$. Its purpose to prevent the contour contains isolated points which are not consistent with the shape.

The external energy takes into account the characteristics of the processed images. Among the existing external energy E_ext, we include the energy gradient E_grad (the first derivative of the image) Equation.(8).

$$E_{ext} = E_{grad} = \int_0^1 \nabla I ||v(s)||^2 ds \quad (8)$$

3.2 Minimization Energies

The energy minimization process consists on minimizing the distance between contour points. To avoid the high retraction between points. Williams and Shah (Rameau, 2011) proposed to use the difference in distance between points to replace the average distance D_{avg}. The continuity and curvature energies are defined respectively as follows Equation (9) and (10).

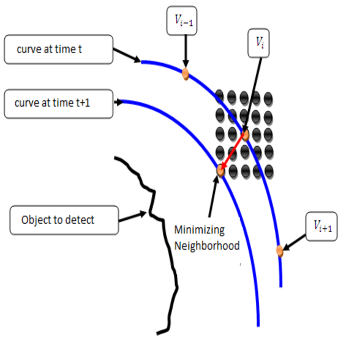


Figure 2: Contour evolution.

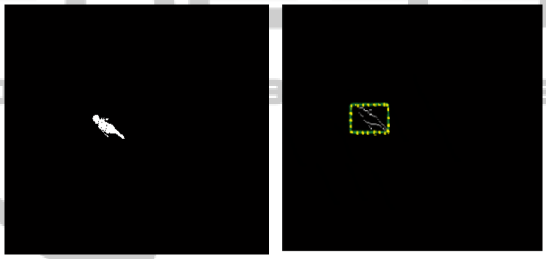
$$E_{cont} = \left| D_{Avg} - \sqrt{(x_i - x_{i-1})^2 - (y_i - y_{i-1})^2} \right| \quad (9)$$

$$E_{curv} = \sqrt{(x_{i-1} + 2x_i + x_{i+1})^2 - (y_{i-1} + 2y_i + y_{i+1})^2} \quad (10)$$

The minimization process is developed to find iteratively the minimum index image gradient value in the neighbourhood of each contour point (Figure. 2).

3.3 Results

We propose two examples to test the snake method for tracking in perspective images. The "WALK" sequence(90 frames) and the "CUP" sequence (60 frames). The first operation is to detect our object. Background subtraction illustrated in figure.3



(a) Object detected by background substraction (b) Initialization contour

Figure 3: Object detection and initialization contour.

(a) Object Tracking (walk sequence)

(b) Object Tracking (Cup sequence)

Figure 4: Object Tracking.

We choice $\alpha = 1.2$, $\beta = 1$, and $\gamma = 1.2$. The obtained results figure. 4 correspond perfectly to our needs. With "WALK" sequence, We obtained a detection time for the first frame 1.05 seconds and a mean tracking time for other images 0.43s. Using "CUP" sequence we obtained a detection time of 0.51s and 0.41s time tracking. Given that the processing was

done in an environment of Pc Core2duo 2.4G, 2G of memory and 1G graphics.
Object tracking in perspective images gave good results for each image of the sequence through the active contours. On the other side, in this method we have limitations. We find on the one hand the choice of parameters α, β, and γ, we have to solve many experiments that require time. On the other hand, we can keep the error if it occurred in the object tracking because the position of contour points is saved.

4 OMNIDIRECTIONAL SNAKE FOR TRACKING

The adapted tracking in omnidirectional images amounts to adapt the process in perspective images. We include the various operators developed in this algorithm.

- The Gaussian filter is applied to reduce the noise in images sequence.
- The subtraction background algorithm used in object detection.
- The energies minimization in the spherical neighbourhood of each contour points used for spherical tracking in spherical omnidirectional images.

4.1 Spherical Gaussian Filtering

We introduce the Gaussian function on the sphere as follows (Antoine and Vandergheynst, 1999) reads:

$$G_s(\theta,\varphi) = \frac{1}{2\,\sigma^2} e^{-\frac{1}{2\,\sigma^2}\left(\frac{cotg^2(\frac{\theta}{2})}{t}\right)} \tag{11}$$

We apply a Gaussian filter based on the point rotation defined in (Daniilidis et al., 2002) for the omnidirectional image smoothing. In the sphere, we applied a convolution (Equation.(13)) between a spherical Gaussian (Equation.(11)) and the spherical image I. We embed the sphere in R^3 and write an element $P(\cos(\varphi)\ \sin(\theta), \sin(\varphi)\ \sin(\theta), \cos(\theta))$. Rotations in R^3 will be parametrized by Euler angles such that any $R \in SO(3)$ will be written as :

$$R = R_z(\varphi)\, R_y(\theta)\, R_x(\psi) \tag{12}$$

where R_y and R_z denote rotation about the y, and z axis, respectively. The convolution will be defined as:

$$(I * G_s)(P) = \int f(R\, n_0)\, g\left(R^{-1}P\right) dR \tag{13}$$

$n_0 = (0,0,-1)$ is half sphere south pole, and $dR = \sin(\theta) d\theta\, d\varphi$.

4.2 Spherical Object Tracking

4.2.1 Spherical Neighbourhood

We defined the new spherical neighbourhood:

$$N_s = \left(|\delta\theta| \leq \frac{1}{N},\ 2\pi - \frac{1}{M} \leq \delta\varphi \leq \frac{1}{M}\right) \tag{14}$$

N et M are the neighbourhood orders.
In our algorithm, we defined the neighbourhood defined by size block 5. That means each contour point has 25 neighborhood. The shape of the spherical block is represented in figure. 5.

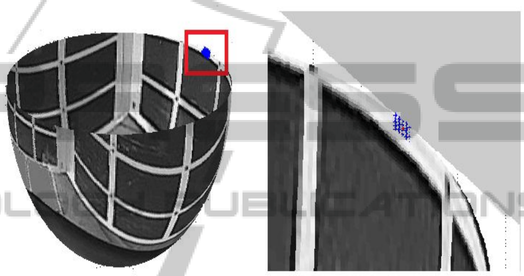


Figure 5: Example of spherical neighbourhood.

4.2.2 Spherical Gradient

In our algorithm, we defined a spherical gradient (image, continuity, and curvature) For the image energy, we apply a spherical contour detection by Sobel filter in the sphere.
first, Sobel proposed filter based on using the mask filtering (Geyer and Daniilidis, 2001) in u and v is defined by:

$$\frac{\partial I}{\partial u} \approx \frac{1}{4}\begin{pmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{pmatrix} \tag{15}$$

$$\frac{\partial I}{\partial v} \approx \frac{1}{4}\begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix} \tag{16}$$

In practice, Daniilidis in (Daniilidis et al., 2002), have effects a variables change defined by:

$$I(\theta,\varphi) = I(u(\theta,\varphi), v(\theta,\varphi)) \tag{17}$$

$$\frac{\partial I}{\partial \theta} = \frac{\partial I}{\partial u} * \frac{\partial u}{\partial \theta} + \frac{\partial I}{\partial v} * \frac{\partial v}{\partial \theta} \tag{18}$$

$$\frac{\partial I}{\partial \varphi} = \frac{\partial I}{\partial u} * \frac{\partial u}{\partial \varphi} + \frac{\partial I}{\partial v} * \frac{\partial v}{\partial \varphi} \tag{19}$$

where u and v are defined in Equation.(2). The spherical gradient can be expressed as : Equation.(20):

$$(\overrightarrow{\nabla I_s} = (\frac{\partial I}{\partial \theta}, \frac{1}{\sin(\theta)^2} * (\frac{\partial I}{\partial \varphi}))) \tag{20}$$

where I_s is the spherical image.

4.2.3 Spherical Energies

From Equation.(20), energie can be expressed based on spherical point.
The external or image energy is presented by the *normalized spherical gradient* in θ and φ. This energie is expressed in Equation.(21), where the result is illustrated in figure.6.

$$E_{xtS} = E_{gradS} = \int_0^1 \nabla I_s \|V(S)\|^2 ds \tag{21}$$

where $V(S) = Ps(\theta,\varphi)$.

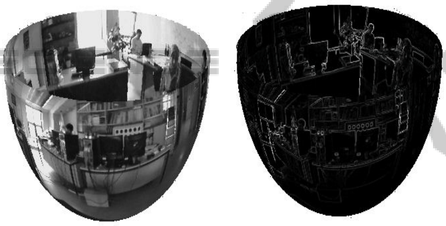


Figure 6: Spherical Sobel (image energy).

Thus, we calculate spherical continuity and curvature energies by a distance between contour points in the half-sphere. This distance have determined by a *3D euclidean distance* in linear case because points are close together using (in continuity energy case) the average distance D_Avg (Wiliams and Shah, 1992).

$$E_{ctS} = |D_Avg - ((x_i - x_{i-1})^2 - (y_i - y_{i-1})^2 - (z_i - z_{i-1})^2)|^{\frac{1}{2}} \tag{22}$$

$$E_{cvS} = ((x_{i-1} + 2x_i + x_{i-1})^2 - (y_{i-1} + 2y_i + y_{i-1})^2 - (z_{i-1} + 2z_i + z_{i-1})^2)^{\frac{1}{2}} \tag{23}$$

The Total energy defined in Equation.(24).

$$E_{TotS} = \sum_{i=1}^{N} (a * E^{pi}_{intS} + b * E^{pi}_{extS}) \tag{24}$$

The total energy minimization is formed in the neighbourhood of each point of the contour. The neighbour that minimizes the energy will be the next contour point initial.

$$Ei_{min} = Arg_{min}(Ei_{TotalS}(Pi(\theta,\varphi))_{N_s}) \tag{25}$$

5 EXPERIMENTS AND RESULTS

To illustrate our contribution, we present the spherical active contour on synthetic and real images. we'll just present the snake on the space of the spherical image, since no other comparison can be made in our context.

5.1 Spherical Tracking: Synthesis Images

We apply edge detection to initialize the points contours from the outline of our object before apply the minimization algorithm. In figure.7, we show object tracking (spherical form) in images obtained using POV-RAY software.

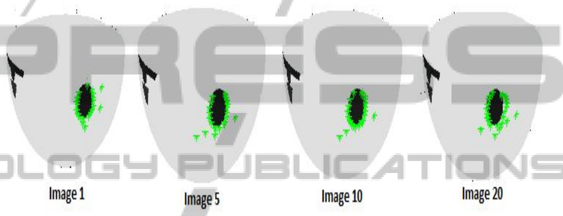


Figure 7: Tracking result -1-.

5.2 Spherical Tracking: Laboratory Images

We obtained the result in "Cata" sequence (780 images) figure 8 and 9. We show the catadioptric and spherical image equivalent with spherical points snake in object (card) tracking.

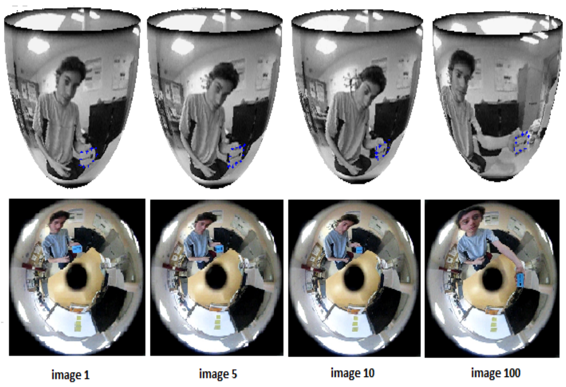


Figure 8: Tracking result -2-.

We conclude from the obtained results, that using of active contours in tracking gives results promoting in terms of edge detection and tracking such as convergence of the algorithm in minimization of the energy functional. (For the minimization algorithm.

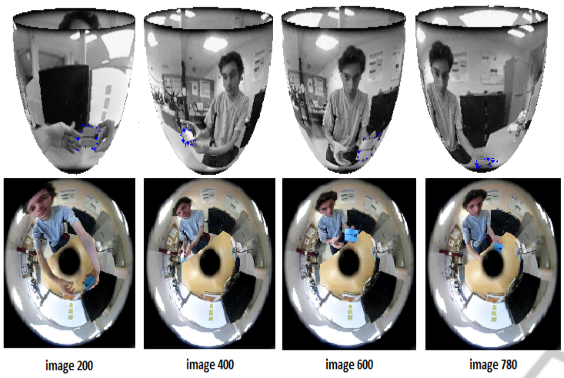


Figure 9: Tracking result -3-.

6 CONCLUSIONS

In our spherical tracking, a first object detection based on background subtraction is applied to the starting image. The minimization algorithm to the others images is applied. Using the adapted process and projection approach, the object contour is perfectly tracked in the equivalent half sphere. The tracking time is about 0.41 seconds and the detection consumes 0.34 seconds. We conclude from the obtained results, that using of snake in tracking gives results promoting in terms of edge detection and tracking such as the algorithm convergence in minimization of the energy functional. For the minimization algorithm, we want to specify two stop criterion, corner number and image energy threshold. The corner conditions are verified when the coefficient of rigidity β is equal to zero. Using snake in tracking is the most used approachs in video surveillance due to the extensibility and ability of recognition for both object shape and orientation. In addition, it's adapted well to object size changes in catadioptric image. However, this method is limited mainly by the choosing of the energy parameters and also occurred error by the minimization algorithm.

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