The TAOS II project

Preliminary results of a learning algorithm to detect stellar ocultations

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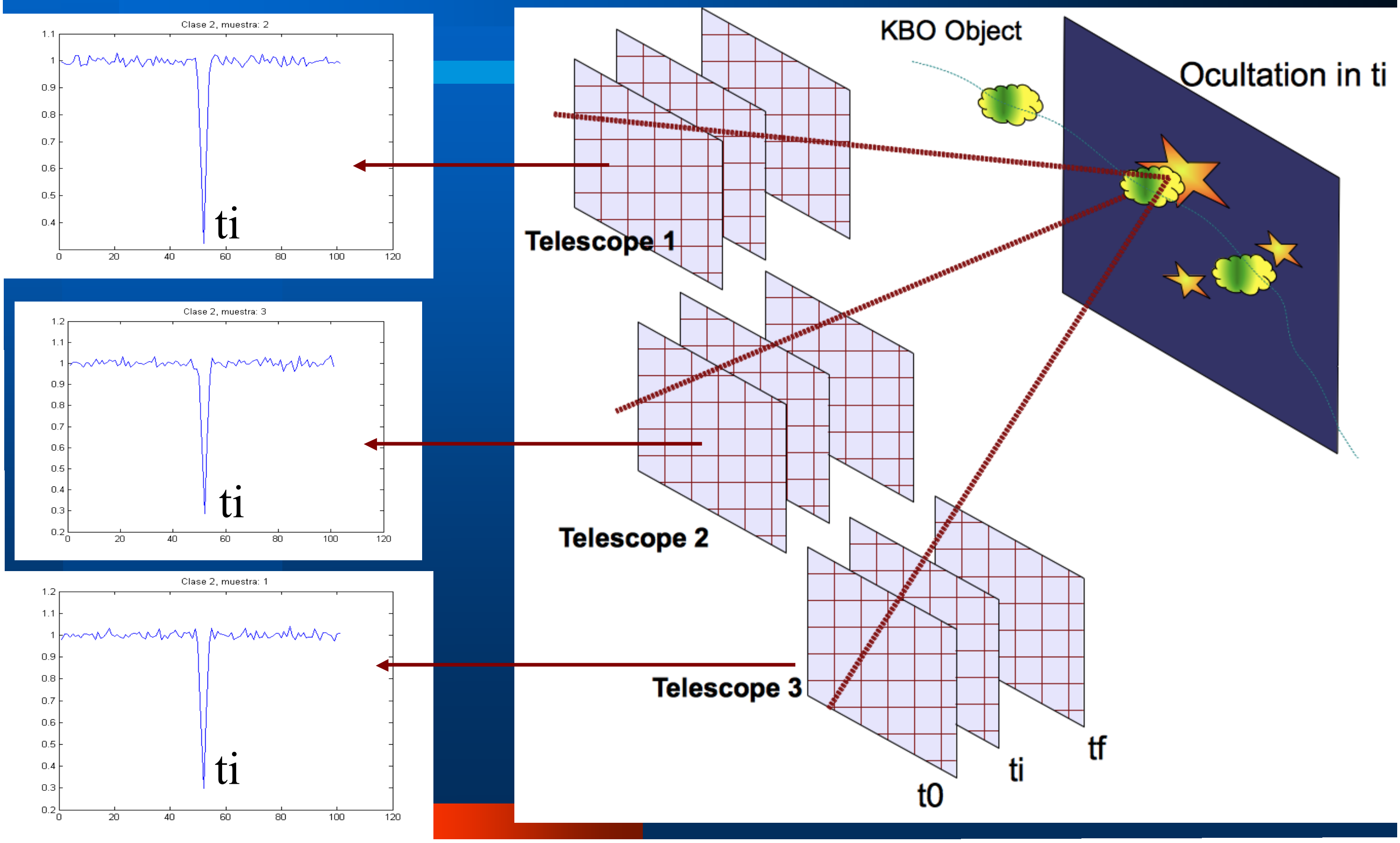
Overview

- We use simulated diffraction patterns produced by the trans-Neptunian objects
- Our problem is to classify this type diffraction patterns.
- We extract three type of feature:
  - statistical,
  - differential operators
  - evolved interest point detector. Then,
- We use Support Vector Machine (SVM) approach as our classifier for occultation detections.
- For a set of 120 synthetic signals for the training process, 60 for the test stage, two classes of occultation and one with pure noise, our learning algorithm correctly detected 96% of the events.

Learning occultation algorithm



Learning occultation algorithm

Suppose that I have a set of the synthetic diffraction occultation pattern of an object in the Kuiper Belt.

$$\gamma_i(r, a, b_j, m, e, s)$$

r is the object diameter; ***a*** is the earth distance, ***bj*** are different impact factors; ***m*** is the magnitude of the star; ***e*** is the spectral type of the star and ***s*** is the sample rate. Also we need to add some random noise such as

$$\Gamma_i = \gamma_i(r, a, b_j, m, e, s) \oplus \eta(.)$$

Learning occultation algorithm

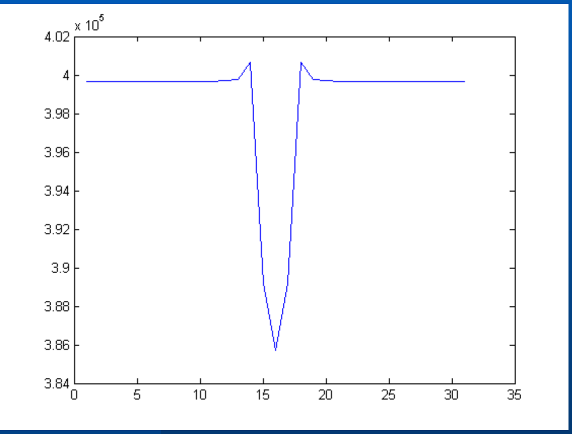
Then, our problem consists to finding a set of n independent features

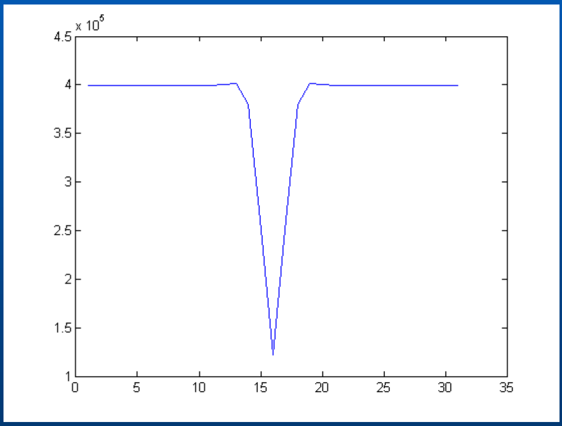
$$\tau_k = f_k(\Gamma_1, \Gamma_2, \Gamma_3)$$

related with ***fk*** functions or relations, so that the set of n features $\{\tau_1, \tau_2, \cdots, \tau_{k1}, \cdots, \tau_n, y_m\}$ are associated to one class of occultation y_m

Learning occultation algorithm

We have 2 class of occultation and non occultation signal (a pure noise signal).





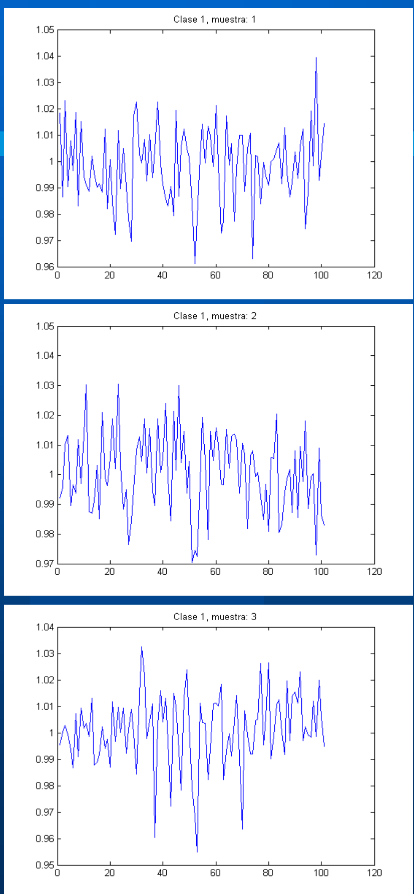
Label Class: 1
Diameter: 1 Km
Distance: 43 AU
Magnitude: 7
Transverse vel.: 25.425 km/s
LightCurve sampling: 10.0 Hz

$$\gamma_i(r,a,b_j,m,e,s)$$

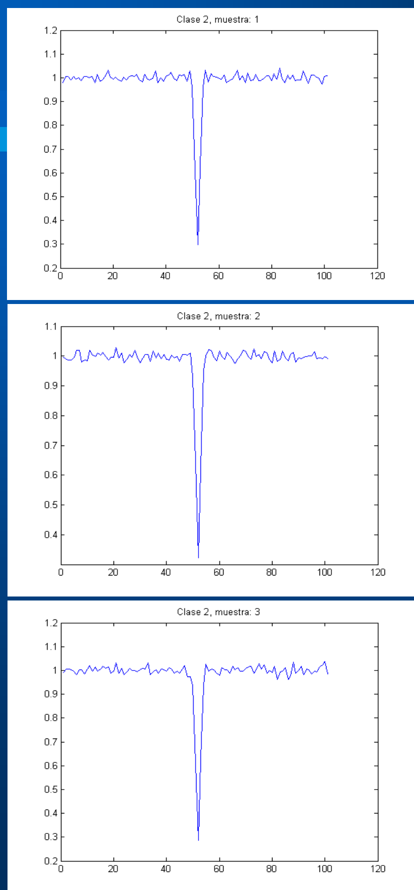
Label Class: 2
Diameter: 5 Km
Distance: 43 AU
Magnitude: 7
Transverse vel.: 25.425 km/s
LightCurve sampling: 10.0 Hz

$$\Gamma_i = \gamma_i(r, a, b_j, m, e, s) \oplus \eta(.)$$

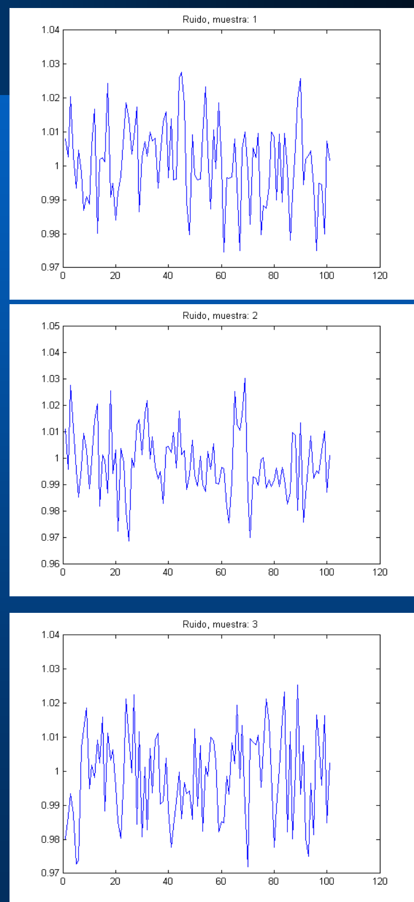
Class 1



Class 2



Class 3: non event



Features

We are include 3 type of features

- Statistics
- Differentials and Gaussian blur
- Interest Point Operators according to Trujillo & Olague 2008

mean $$\tau_1 = \frac{1}{T}\sum^{T}\Gamma_i$$

variance $$\tau_2 = \frac{1}{T-1}\sum^{T}(\Gamma_i - \overline{\Gamma})^2$$

standard deviation $$\tau_3 = \sqrt{\frac{1}{T-1}\sum^{T}(\Gamma_i - \overline{\Gamma})^2}$$

$$\tau_4 = \max imun(\Gamma)$$

In the next feature we are compute the operator using a kernel of 3 and 5 samples.

First derivative

$$\tau_{5,6} = \max\left(\frac{\partial \Gamma}{\partial t}\right)$$

Second derivative

$$\tau_{7,8} = \max\left(\frac{\partial^2 \Gamma}{\partial t^2}\right)$$

Gaussian smooth operators.

$$\tau_{9,10} = \max\left(\Gamma * G_{\sigma=0.5}\right)$$

$$\tau_{11,12} = \max\left(\Gamma * G_{\sigma=1}\right)$$

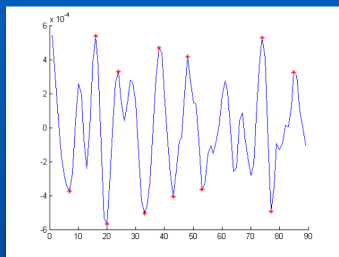
$$\tau_{13,14} = \max\left(\Gamma * G_{\sigma=2}\right)$$

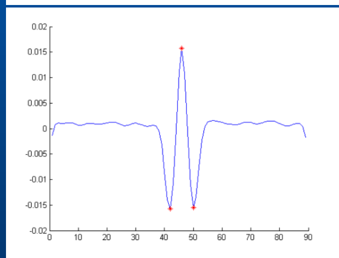
$$\tau_{15,16} = \max\left(\Gamma * G_{\sigma=1} - \Gamma * G_{\sigma=0.5}\right)$$

$$\tau_{17,18} = \max\left(\Gamma * G_{\sigma=2} - \Gamma * G_{\sigma=1}\right)$$

$$\tau_{19,20} = \max((\Gamma * G_{\sigma=2} - \Gamma * G_{\sigma=1}) - (\Gamma * G_{\sigma=1} - \Gamma * G_{\sigma=0.5}))$$

The next feature are interest points detector. We employ a nom maximum suppression schema (NMS) and count the numbers of interest point and its variance (var). We compute for a kernel of 3 and 5 pixels





$$\tau_{21,22,23,24} = (NMS,\mathrm{var})\left(G_{\sigma=2} * (G_{\sigma=2} * \Gamma - \Gamma)\right)$$

$$\tau_{25,26,27,28} = (NMS,\mathrm{var})\left(G_{\sigma=2} * |\Gamma - G_{\sigma=2} * \Gamma|^2\right)$$

$$\tau_{29,30,31,32} = (NMS,\mathrm{var})\left(G_{\sigma=1} * \left(\frac{G_{\sigma=1} * \Gamma}{(G_{\sigma=1} * G_{\sigma=1} * \Gamma)^3}\right)\right)$$

$$\tau_{33,34,35,36} = (NMS,\mathrm{var})\left(\frac{G_{\sigma=2} * \Gamma^{\frac{3}{2}}}{(G_{\sigma=1} * \Gamma)^{\frac{9}{4}}}\right)$$

$$\tau_{37,38,39,40} = (NMS,\mathrm{var})\left(G_{\sigma=2} * G_{\sigma=2} * [(G_{\sigma=2} * \Gamma)(G_{\sigma=2} * G_{\sigma=1} * \Gamma - \Gamma)]\right)$$

Results

- 3 Classes
- 40 signals in the training stage per class
- 20 signals per class for test

True\detected	1	2	3
1	20	0	0
2	0	20	0
3	1	0	19

Collaborators

- Students of the summer school of Astronomy.
  - Arturo Osorio
    - Ingeniería en Física. UAM Azcapotzalco
  - Miguel Angel Teran
    - Licenciatura en Física. UABC Ensenada

Some Author References

Hernandez, B., Olague, G., Hammoud, R., Trujillo, L., and Romero, E. (2007) Visual Learning of Texture Descriptors for Facial Expression Recognition in Thermal Imagery. Computer Vision and Image Understanding . Elsevier Science. Vol. 106(2-3) pp 258-269.

Olague, G. and Hern疣dez, B. (2005) A New Accurate and Flexible Model Based Multi-corner Detector for Measurement and Recognition, Pattern Recognition Letters, Vol. 26(1) pp. 27-41

Olague, G., Hammoud, R., Trujillo, L., Hernandez, B., and Romero, E.. Facial Expression Recognition in Nonvisual Imagery, In Riad I. Hammoud (Eds), Augmented Vision Perception in Infrared, Algorithms and Applied Systems. Springer-London, Adv. Pattern Recognition Series, Chapter 10, pages 213-239, on line January 1, 2009.

Olague, G., Hernandez, B. Autonomous Model-based Corner Detection using Affine Evolutionary Algorithms, In S. Cagnoni, E. Lutton, and G. Olague (Eds), Genetic and Evolutionary Computation for Image Processing and Analysis, Hindawi Publishing Corporation, Vol. 8, pp. 135-155, 2008.

Olague, G., Hernadez, B. Flexible Model-based Multi-corner Detector for Accurate Measurements and Recognition, 16th International Conference on Pattern Recognition. IEEE Computer Society Press. Vol. II, pp. 578-583. August 11-15, 2002, Quebec, Canada.

Olague, G., Hernandez B, Dunn, E. Hybrid Evolutionary Ridge Regression Approach for High-Accurate Corner Extraction, IEEE Computer Society Conference on Computer Vision and Pattern Recognition. June 16-22, 2003, Madison, USA.

Trujillo, L., Olague, G., Hammoud, R., and Herandez, B. Automatic Feature Localization in Thermal Images for Facial Expression Recognition. 2 nd. Joint IEEE International Workshop on Object Tracking and Classification in and Beyond the Visible Spectrum. OTCBVS 2005. In Conjuction with CVPR 2005.

Thank you!