

Hipparcos Variable Star Detection and Classification Efficiency

P. Dubath, I. Lecoœur-Taïbi, L. Rimoldini, M. Süveges, J. Blomme, M. López, L. M. Sarro, J. De Ridder, J. Cuypers, L. Guy, K. Nienartowicz, A. Jan, M. Beck, N. Mowlavi, P. De Cat, T. Lebzelter and L. Eyer

Abstract A complete periodic star extraction and classification scheme is set up and tested with the Hipparcos catalogue. The efficiency of each step is derived by comparing the results with prior knowledge coming from the catalogue or from the literature. A combination of two variability criteria is applied in the first step to select 17 006 variability candidates from a complete sample of 115 152 stars. Our candidate sample turns out to include 10 406 known variables (i.e., 90% of the total of 11 597) and 6600 contaminating constant stars. A random forest classification is used in the second step to extract 1881 (82%) of the known periodic objects while removing entirely constant stars from the sample and limiting the contamination of non-periodic variables to 152 stars (7.5%). The confusion introduced by these 152 non-periodic variables is evaluated in the third step using the results of the Hipparcos *periodic* star classification presented in a previous study (Dubath et al. [1]).

1 Introduction

Current and forthcoming photometric surveys are monitoring very large numbers of astronomical targets providing a fantastic ocean for fishing interesting variable objects. However, because of the large numbers involved, their extraction requires the use of fully automated and efficient data mining techniques. In this contribution, we use the Hipparcos data set to investigate the performance of a complete and automated scheme for the identification and the classification of periodic variables. As shown in Fig. 1, we study a three step process. In the first step variable candidates are separated from the objects most likely to be constant. This saves significant processing time as period search is performed only in the subset of variable candidates. The validity of the detected periods is established in the second step, which sepa-

P. Dubath
Observatoire astronomique de l'Université de Genève/ISDC, ch. d'Écogia 16, 1290 Versoix,
Switzerland e-mail: Pierre.Dubath@unige.ch

rates truly periodic from non-periodic objects. The third step is the classification of periodic variables into a list of types (only a sub-set of them are shown in Fig. 1). This step is presented in details in Dubath et al. [1]. To avoid unnecessary repetition, this first paper is referred to for a full description of the classification attribute calculation and of the details of the random forest methodology.

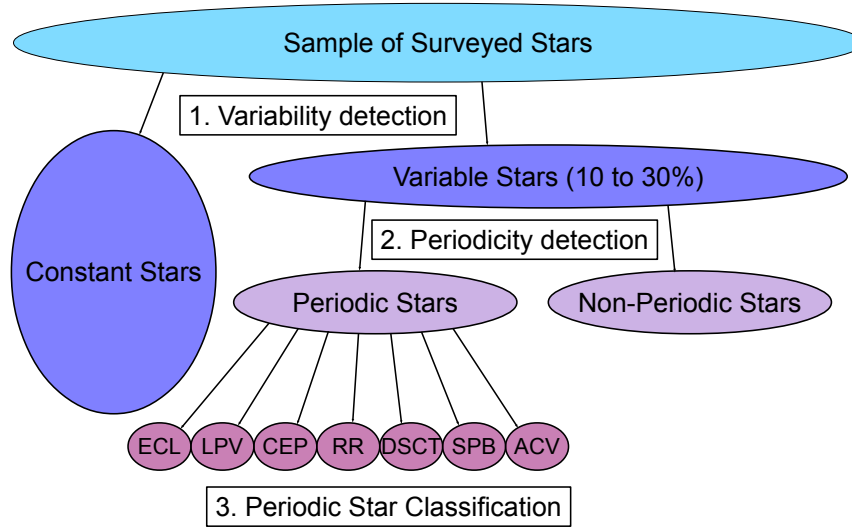


Fig. 1 Illustration of the steps used in this study to identify and classify variable sources

This three step organisation represents a particular option. Alternatives are also being considered, but they are outside the scope of this contribution as is the classification of non-periodic variables which is the subject of another study (Rimoldini et al., in preparation).

2 Variability Detection

In order to select variable star candidates, a number of variability criteria are computed from the Hipparcos light curves¹. These criteria are all, in one way or another, characterizing an excess of scatter compared to the one expected from random noise. Some of them rely on the noise estimations while others do not. P-values are computed for each of the tests. The star is accepted as a variable candidate if the p-value is smaller than a specified threshold.

¹ Only data point with quality flags 0 and 1 have been used in the light curves and stars with light-curves with less than 5 good data points are discarded.

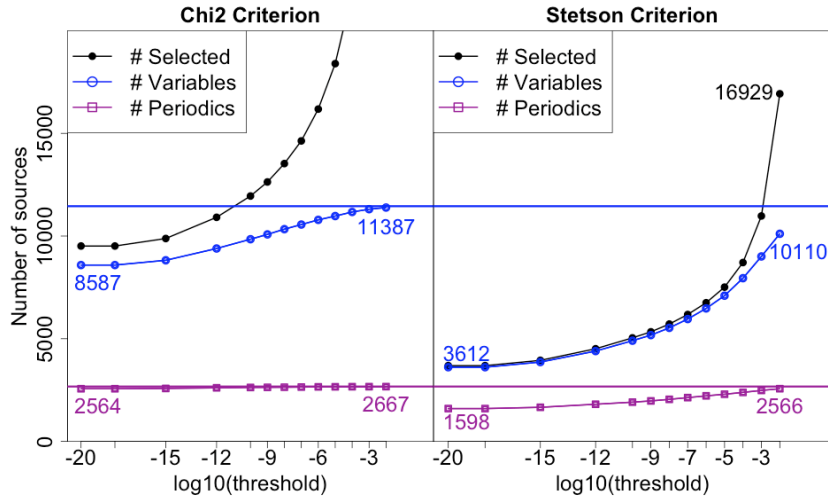


Fig. 2 Number of stars selected using the chi-square criterion (left) and the Stetson [2] one (right) as a function of the p-value threshold. The total numbers of selected stars are displayed in black, while the fraction of periodic and variable stars are shown in magenta and blue, respectively. The numbers of variable stars drawn in blue include the contribution of periodic and non-periodic objects. The difference between the blue and the black curves indicates the amount of contamination from non-variable stars. The two horizontal lines indicate the total number of periodic stars (2672 in magenta) and of variable stars (11 453 in blue). The complete sample includes 115 152 stars.

Figure 2 shows the number of selected sources as a function of the p-value threshold obtained from a chi-square criterion in the left panel and from an alternative criterion proposed by Stetson [2] in the right one.

As expected, the number of selected stars increases with larger p-values thresholds in both panels. The optimum threshold maximizes the numbers of selected true variables while limiting the contamination by false positives (i.e., by constant stars). The chi-square criterion is efficient at finding variables, but it also includes a large number of false positives, even when the threshold is extremely small. This suggests that Hipparcos photometric errors may be slightly underestimated. The Stetson criterion is quite efficient for periodic variables and it limits better the number of false positive detections, but it misses more non-periodic variable stars.

Figure 3 shows a comparison of the numbers of stars selected using different variability criteria tested with a particular near-optimum p-value threshold. The variability criteria tested include (1) the chi-square criterion, (2) the skewness and (3) the kurtosis of the magnitude distributions, the (4) Abbe criterion (e.g., see Strunov [3]), (5) the interquartile range, (6) the Stetson criterion, (7) the outlier median criterion and (8) the union of the Stetson and interquartile criteria.

This figure shows again that the chi-square is the most efficient criterion at identifying variable stars, but that it also includes the largest contribution of false positive detections. A final sample of 17 006 variable candidates (i.e, 14.8% of the total) is

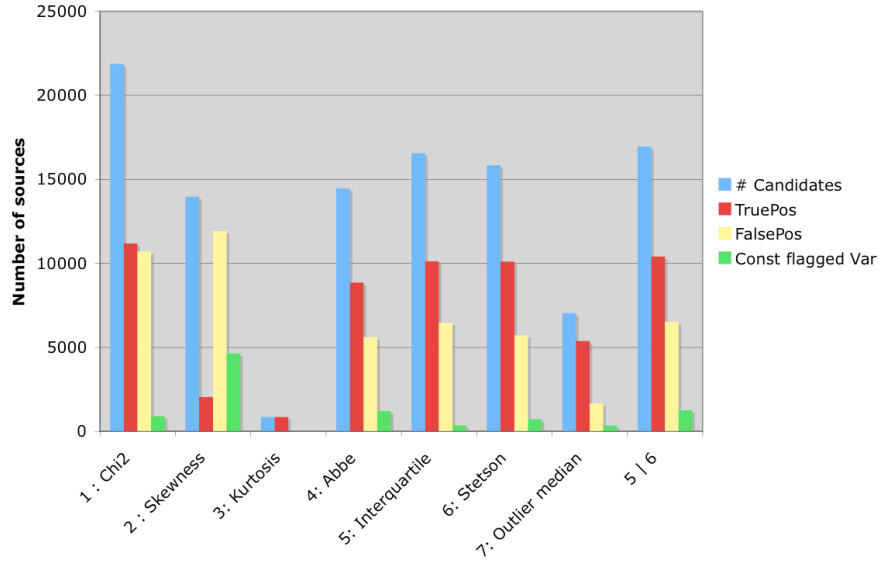


Fig. 3 Comparison of the numbers of stars selected using different variability criteria and a particular near-optimum p-value threshold. The total numbers of variable candidates appear in blue, red bars show the number of candidates flagged in the Hipparcos catalogue as variables (i.e., the true positive detections), yellow bars indicates the number of false positives. The fraction of false positives flagged as “constant” in the Hipparcos catalogue are shown in green.

formed by merging the Stetson and the interquartile selections obtained with p-value thresholds of 10^{-2} and 10^{-3} , respectively. This sample is used in the subsequent steps of this study.

3 Periodicity Detection

Fig. 1 indicates that periodicity detection is the second step. This figure might however be misleading as it assumes that the first step is perfect. In reality, the second step starts with a sample of variable star *candidates*, which includes a number of constant objects. With the knowledge of the Hipparcos catalogue², we know quite precisely what mixture of stars is included in our selection. Out of the 17 006 candidate sample, (1) 2657 stars are flagged as periodic in the Hipparcos catalogue (flag H52), (2) 6954 as unsolved³, (3) 794 micro-variable, (4) 762 as constant and (5) 4360 are not flagged, because they were not considered variable nor constant with

² <http://www.rssd.esa.int/index.php?project=HIPPARCOS&page=Overview>

³ Stars flagged as “Unsolved” have Hipparcos light curves from which it was not possible to derive significant evidence for a period. They may include periodic stars with light-curves of insufficient quality or truly non-periodic sources.

any degree of confidence⁴. These stars are used to train and test the performance of a random forest supervised classifier for identifying periodic variables.

Using the procedures and criteria described in section 3 of Dubath et al. [1], a good period is obtained for 2323 of the 3022 stars with a known period included in our 17 006 star sample (i.e., a good period recovery rate of 77%). There are 357 stars flagged as periodic with wrong period values. Those are eliminated from our training set as well as the 20 “unsolved” stars for which a good period value is found.

A large number of attributes are computed and the procedure presented in section 4 of Dubath et al. [1] is followed to rank and select the most important attributes. Figure 4 displays the results of a series of ten experiments of 10-fold Cross-Validation (CV), i.e., 100 experiments for each attribute number.

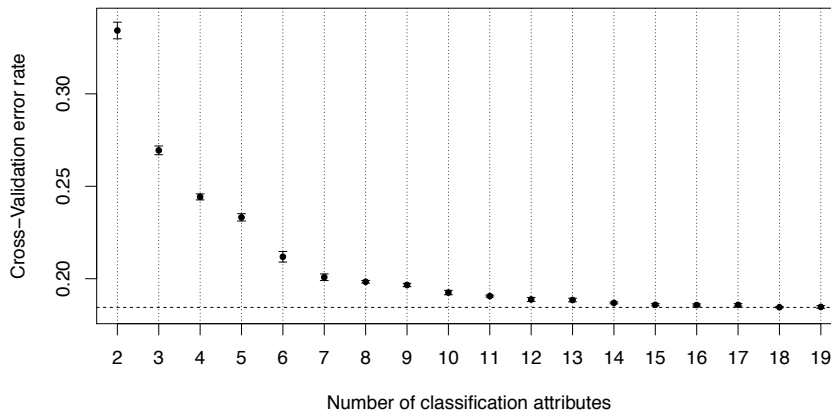


Fig. 4 Evolution of the Cross-Validation (CV) error rate as more and more attributes are added into the classification process. In the different CV experiments (hundred for each attribute number), the exact list of attributes used to estimate the error rate is not always exactly the same (see Fig. 5).

Figure 4 shows that the three most important attributes already drive the mean error down to 27%, which reduces to 20% with 7 attributes. The mean error continues to decrease slowly until it reaches a plateau of 18.5%. Using more than about 15 attributes does not lead to further significant improvements.

Figure 5 displays the ranking of the most important attributes in the CV experiments. Fig. 4 and 5 should be read together. While Fig. 4 shows that experiments done with 3 attributes result in a mean error rate of 27%, Fig. 5 indicates that most

⁴ 662 stars flagged as “R” (for revised color index) and 816 stars flagged as “D” (duplicity-induced variability) in the Hipparcos catalogue are not included in our training set (see page 121 of the Hipparcos catalogue).

of the time the 3 most important attributes are those labelled (a), (b), and (c). Numbers in this figure indicate the number of time that the attribute has a particular rank in the series of 100 experiments.

a. Stetson criterion	100						
b. $\text{Log}_{10}(\text{range})$	68	23	9				
c. Normalized p2p scatter	18	43	36	3			
d. QSO_{var} criterion	13	31	47	9			
e. $\text{Log}_{10}(\text{QSO probability})$	1	3	8	80	8		
f. Period search FAP				8	50	33	
g. P2p scatter: P/raw					35	50	
h. 0.1 to 1 day variance					7	17	
		1	2	3	4	5	6
		Attribute rank					

Fig. 5 This figure shows the ranking of the most important attributes in the ten series of 10-fold cross-validation experiments.

Below we provide a short description of the most important attributes displayed in Fig. 5.

- a Stetson criterion – Stetson variability index [2] pairing successive measurements if separated by less than 0.05 days. This time interval is optimized to be long enough to make many pairs while remaining much shorter than typical period values.
- b $\text{Log}_{10}(\text{range})$ – decadic log of the range of the raw time series magnitudes.
- c Normalized p2p scatter – Point-to-point scatter computed on the folded time-series normalized by the mean of the square of the measurement errors.
- d QSO_{var} criterion – Reduced χ^2 of the source variability with respect to a parametrized quasar variance model (denoted by χ^2_{QSO}/ν in Butler & Bloom [4]).
- e $\text{Log}_{10}(\text{QSO probability})$ – Log_{10} of a quantity defined by Eq. 8 in Butler & Bloom [4].
- f Period search FAP – False-alarm probability associated with the maximum peak in the Lomb-Scargle periodogram.
- g P2p scatter: P/raw – Point-to-point scatter from folded time-series normalized by the same quantity computed on raw time-series.
- h Variance within 0.1 to 1 day intervals – The average of absolute magnitude variations on time scales from 0.1 to 1 days.

Figure 6 shows the confusion matrix obtained from the out-of-bag samples of a 2000-trees random forest classification. Out of the 2300 periodic stars with good periods, 1881 (82%) are correctly identified while 419 (18%) are missed, mostly appearing in the “unsolved” category. Remarkably, only 152 stars (134 unsolved, 9 micro-variables and 9 stars without flags) are wrongly classified as “periodic”, resulting in a total contamination of the periodic type of 7.5%. There is also no confusion between “constant “ and “periodic” types.

	Constant	Microvariable	Unsolved	Periodic		
Constant	207	554	1		Constant	
Microvariable	113	3752	93	393	9	Microvariable
Unsolved		321	313	151	9	Unsolved
Periodic		514	69	6217	134	Periodic
		15	22	382	1881	

Fig. 6 Confusion matrix obtained with the out-of-bag samples in a 2000-trees random forest classification.

4 Impact on periodic star classification

The classification of the Hipparcos periodic variable stars is the subject of a previous study (Dubath et al. [1]). The confusion matrix obtained in that study is displayed in Fig. 7. This figure represents however an optimistic picture as this sample only contains the best known stars, for which we have relatively clean light-curves. It is very difficult to evaluate accurately the extent of the expected degradation when using this model to classify other stars. Some indications can however be derived in two different ways.

First, the classification model derived from the training set can be applied to the sample of Hipparcos stars with uncertain types from the literature. The results of this process is shown in Fig. 10 and 11 by Dubath et al. [1], where a relatively mild confusion is observed and evaluated.

Second, the current study shows that any sample of periodic stars is expected to be contaminated by non-periodic stars because of the imperfection of the two preliminary steps, namely variability and periodicity detections. This contamination is evaluated to about 7.5% in last section (see Fig. 6). The 152 stars wrongly identified as periodic can be classified using a periodic classification model to evaluate more precisely the contamination in terms of periodic types.

A 10-fold cross-validation experiment is carried out to extract the variables wrongly classified as periodic: 150 stars, including 133 "Unsolved", 8 "Micro-variable" and 9 with no flag. These numbers slightly differ from the corresponding ones in Fig. 6 due to the randomness involved in random forest classification. The classification model from Dubath et al. [1] is then used to predict periodic types for these stars.

EA	EB	EW	ELL	LPV	RV	CWA	CWB	DCEP	DCEPS	CEP(B)	RRAB	RRC	GDOR	DSCT	DSCTC	BCEP	SPB	BE+GCAS	ACYG	ACV	SXARI	BY+RS	
214	13									1													EA
19	191	28	2	1				2					1		4		3		2	2			EB
	30	76							1														EW
	14			1									1		1		3				5	2	ELL
					285																		LPV
	1				1			2	1														RV
	2					1		5															1 CWA
	1						2	2	1														CWB
								183	5	1													DCEP
	1							11	17													2	DCEPS
	1							4		6													CEP(B)
	1										69	1						1					RRAB
	2	4									1	12			1								RRC
													27										GDOR
	1	1								1					32	12							DSCT
	1													1	77						2		DSCTC
	1	1													1	26	1						BCEP
			1													1	74		1	4			SPB
1									1								5		2	4			BE+GCAS
	1																	1	13	2		1	ACYG
	3								1				1				6			66			ACV
	2																2			3			SXARI
	1							1														33	BY+RS

Fig. 7 Confusion matrix obtained by Dubath et al. [1] for the Hipparcos periodic variable stars.

The predicted types for the 150 stars turn out to include 125 Long-Period Variables (LPVs), 9 RR Lyrae of type AB, 6 Delta Scuti and eclipsing binaries of type EA (5) and EB (5). The LPV classification prediction for 125 stars could easily be understood if they had large amplitude, red color and long (most probably spurious) periods as expected for such kind of stars. However, this is not supported by the data. The understanding of the true nature of these stars requires further investigation.

References

1. Dubath, P., Rimoldini, L., Süveges M. et al., *Mon. Not. R. Astron. Soc.*, **May**, 651 (2011)
2. Stetson, P. B., *Publ. Astron. Soc. Pacific* **108**, 851 (1996)
3. Strunov, V., *Measurement Techniques*, **49**, 755 (2006)
4. Butler, N. R. and Bloom, J. S., *Astronomical Journal*, **141**, 93 (2011)