Apparent non-variable stars from the Kepler mission

E. Paunzen1,2, F. Binder1, A. Cyniburk1, M. N. Duffek1, F. Haberhauer1, C. Heinreichsberger1, H. Kohlhofer1, L. Kueß1, H. M. Maitzen1, T. Saulmann1, A. M. Schanz1, S. Schauer1, K. Schmidt1, A. Tokareva1, and I. Wizani1

1 Department of Astrophysics, Vienna University, Türkenschanzstraße 17, 1180 Vienna, Austria
2 Department of Theoretical Physics and Astrophysics, Masaryk University, Kotlářská 2, 611 37 Brno, Czech Republic

e-mail: epaunzen@physics.muni.cz

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ABSTRACT

Context. The analysis of non-variable stars is generally neglected in the literature. However, such objects are needed for many calibration processes and for testing pulsational models. The photometric time series of the Kepler satellite mission still stand as the most accurate data available today and are excellently suited to the search for non-variable stars.

Aims. We analysed all long-cadence light curves for stars not reported as a variable so far from the Kepler satellite mission. Using the known characteristics and flaws of these data sets, we defined three different frequency ranges where we searched for non-variability.

Methods. We used the Lomb–Scargle periodogram and the false-alarm probability (FAP) to analyse the cleaned data sets of 138 451 light curves. We then used \( \log FAP \geq -2 \) to define a star as ‘non-variable’ in the ranges below 0.1 c/d, 0.1 to 2.0 c/d, and 2.0 to 25.0 c/d, respectively. Furthermore, we also calculated the standard deviation of the mean light curve to obtain another parameter.

Results. In total, we found 14 154 stars that fulfil the set criteria. These objects are mostly cooler than the 7000 K populating the whole main sequence (MS) to the red giant branch (RGB).

Key words. methods: data analysis – catalogs – Hertzsprung–Russell and C–M diagrams – supernovae: general

1. Introduction

One of the essential questions related to studies aimed at describing stellar objects is whether they are all variable. The most commonly given answer is that all stars are variable, but it is only the amplitude that makes a significant difference. The Sun, the closest star to our planet, is a perfect example (Fröhlich & Lean 2004). Its variability amplitude depends on the wavelength region (with more considerable changes at shorter wavelengths). Furthermore, a timescale of about 11 yr, with an amplitude of about 1 mmag, a 27-day rotation period (2 mmag), and five-minute short-scale variations (of 0.15 mmag) have been found. An observer from the outside would measure the superposition of all these variations integrated over the solar surface. It also shows how vital time sampling is for detecting variations on different time scales.

In general, variable stars are at the centre of many scientific studies (e.g. Gaia Collaboration 2019). For example, cepheid variables and their period-luminosity-relations (Leavitt & Pickering 1912) have allowed us to start constructing a distance ladder, which helped explore large regions of the Universe. The periods, amplitudes, and light curve characteristics (Sterken & Jaschek 1996) are as manifold as the underlying physical mechanisms (Percy 2007).

However, it is important not to lose sight of non-variable stellar objects, as they are very much needed for calibrating absolute fluxes and radial velocities (most photometric variable stars also show strong spectroscopic variations). Techniques such as fitting the spectral energy distribution (Bayo et al. 2008) are crucial depending on the non-variability. Many photometric calibrations of the effective temperature and metallicity (Paunzen et al. 2006; Netopil 2017) are based on Galactic field stars. However, the variability of the individual stars is generally neglected. For example, the effective temperature of the Cepheid κ Pavonis varies between 5300 and 6300 K over the pulsational phase (Breitfelder et al. 2015). The paper by Mullally et al. (2022) investigated the impact of stellar variability in the spectrophotometric calibration of the science instruments aboard James Webb Space Telescope. They concluded that variability for cool-type stars cannot be neglected if the full capacities of the instruments are to be achieved. A very useful example of how variable stars change their locations in the colour–magnitude diagram is given in Gaia Collaboration (2019, in their Fig. 11). The authors have stated that this figure represents a first step towards a more global description of stellar variability, namely, by providing new perspectives on the data that can be exploited as variable star classification attributes to improve the classification results appreciably. However, it is much more essential to find the astrophysical parameter space that discriminates between variable and non-variable objects in the same location of the colour-magnitude diagram. Works analysing non-variable stars are quite rare (Schmidt et al. 1974; Kepler et al. 1995; Adelman 2001), for two main reasons: 1) establishing non-variability based on a photometric time series is not straightforward and 2) the demand for such objects is not very high.

We present the results of our analysis of the long-cadence light curves of the Kepler mission. We applied a simple cleaning algorithm, starting with the pre-search data conditioning Simple Aperture Photometry (PDCSAP) files. Based on the published experiences with the Kepler data sets, we have analysed three different frequency domains and calculated Lomb–Scargle
periodograms (LSPs) as well as the false-alarm probabilities (FAPs). These time series data sets are still the most accurate available today.

The final goal is to present a list of non-variable stars in different frequency domains for a given upper limit of the FAP and a mean standard deviation of the cleaned light curve. This set of stars could serve as a basis for calibrating standard fluxes and the comparison of variable stars in the same region of the HRD.

2. Overview: Kepler Space Telescope

The light curves used in this work were obtained by the Kepler Space Telescope, a successful tool launched in 2009 aimed at discovering extrasolar planets and variable stars, until it was shut down in 2018 due to fuel depletion.

The design of the Kepler Space Telescope is pretty simple. It consists of a Schmidt-Telescope with an aperture of 0.95 m and a primary mirror of 1.4 m in diameter. The light of the stars is collected on a focal plane that consists of 21 pairs of CCDs, each CCD having 2200 × 1024 pixels, totalling 95 megapixels on the whole focal plane. The dynamic range of the sensors allowed stars between 9 and 16 mag to be observed. These time series data sets are still the most accurate periodograms (LSPs) as well as the false-alarm probabilities (FAPs). These time series data sets are still the most accurate periodograms (LSPs) as well as the false-alarm probabilities (FAPs). These time series data sets are still the most accurate periodograms (LSPs) as well as the false-alarm probabilities (FAPs).

Additionally, the telescope was rotated every three months to keep the solar panels in the Sun, allowing the telescope to operate appropriately. These different sets are called ‘quarters’. The 9 yr of the mission were divided into two parts, as described below.

Kepler was the original mission from 2009 to 2013 until two of the four reaction wheels stabilising the telescope failed. A field of view (FOV) of around 115 square degrees in the constellations of Cygnus, Lyra and Draco was chosen for this task. Then, K2 started in 2014 and observed 20 different FOVs along the ecliptic, each for about 80 days until the telescope ran out of fuel in 2018. Kepler used two observing modes for its light curve generation (Murphy 2012; Thompson et al. 2016): (1) long cadence (LC): 29.424-min bins of 270 integrations and (2) short cadence (SC): 1-min bins of 9 integrations.

In total, Kepler observed 530 506 stars during its lifetime. Looking at this huge data set, we have around 3000 confirmed exoplanets Akeson et al. (2017) and about as many published papers. While the primary goal of the telescope was to find the above-mentioned planets, its precise photometry allowed it to find many new variable stars. It proved very useful for astronomers working in asteroseismology Gilliland et al. (2010) and with binary stars Rappaport et al. (2013).

3. Target selection

We first selected all stars with long cadence light curves available within the original Kepler mission for our analysis. We did not consider the about 2000 short cadence light curves because they are only a small fraction of the overall data set.

As the next step, we removed all stars already known as variables. For this, we used the catalogue of the Asteroid Terrestrial-impact Last Alert System (ATLAS, Heinze et al. 2018) and the International Variable Star Index (VSX, Watson et al. 2006), along with several works presenting automatic variable star detection routines using Kepler data (Blomme et al. 2010; McNamara et al. 2012; Stello et al. 2013; Bass & Borne 2016; Yu et al. 2016). No further constraints were set. The final sample further processed consisted of 138 451 light curves. As a next step, we investigated the location of the target stars in the Hertzsprung-Russell diagram (HRD).

Berger et al. (2020) presented astrophysical parameters of 186 301 Kepler stars homogeneously derived from isochrones and broadband photometry, Gaia Data Release 2 parallaxes, and spectroscopic metallicities, were available. However, we decided to check these values independently. Therefore, we cross-matched our targets with various catalogues to get the distances needed to calculate the bolometric absolute magnitude ($M_{bol}$). The distances were taken from Bailes et al. (2021), where we used the photometric values since they seem more reliable. Those are available for 106 999 of our targets. To calculate the bolometric correction $BC$, we used the polynomial originally published by Flower (1996) and later refined by Torres (2010). The bolometric corrections were then applied to the absolute Gaia G magnitudes ($M_G$) and the luminosities calculated using $M_{bol} = 4.75$ mag. We relied on the map of Green et al. (2019) for the reddening. The photometric colours Gaia ($BP − RP$) for checking the effective temperatures listed in Berger et al. (2020) were also taken from Gaia Collaboration (2021).

A comparison of our calibrated values and the ones from Berger et al. (2020) resulted in an excellent agreement ($\Delta T_{eff} = 3.8\%$ and $\Delta M_{bol} = 2.9\%$). Such a check is important for the location of stars in the HRD, independent of the calibration procedure used.

As shown in Fig. 1, our target star sample consists mainly of objects cooler than 10 000 K with most stars being solar type objects, also including a significant amount of objects on the subgiant and red-giant branch. No evolved intermediate and high-mass stars have been included.

4. Data preparation

The light curves come in two versions. One is the raw uncorrected flux coming from the telescope (Simple Aperture Photometry, SAP), and the other one has been corrected and already detrended (presearch data conditioning SAP, PDCSAP). For our analysis, we started with the PDCSAP fluxes using only data with optimal quality flags (SAP_QUALITY = 0). We know further processed light curves exist, such as those from Garcia et al. (2011) for asteroseismic analyses. However, all those sets are
Finally, we transformed the fluxes into magnitudes and subtracted the mean magnitude and the observation starting time. These subtractions guarantee a better numerical performance of the time series algorithm because (quadratic) sums are calculated, which could reach a high number for faint magnitudes or large fluxes. The transformation into magnitudes makes a comparison with the ongoing ground-based observations such as The All-Sky Automated Survey for Supernovae (ASAS-SN; Kochanek et al. 2017), Optical Gravitational Lensing Experiment (OGLE; Udalski et al. 2015), and Zwicky Transient Facility (ZTF; Bellm et al. 2019) much easier.

Figure 2 shows the different steps of our data preparation, including the differences between the SAP and PDCSAP fluxes for the faint ($V = 15.545$ mag) star KIC 1293468 (UCAC4 635-069420). The final cleaned light curve consists of 64745 individual data points and has a standard deviation of the mean of 0.61 mmag.

5. Time series analysis

Detecting a strong periodic signal in a time series is usually straightforward. However, when it comes to small amplitudes or the need to statistically prove that a data set consists only of noise, this can become very difficult (Priestley 1988).

In astronomy, we normally deal with a discrete, unevenly spaced, gapped, and finite data set of an independent (time) and dependent (for example, magnitude) variable, including noise. From a mathematical and statistical point of view, those are the most difficult time series to deal with (Subba Rao et al. 1997). The literature shows two different time series methods are commonly used: the Fourier and string-length methods.

The latter is based on very simple assumptions. First, the data are folded into a series of trial periods. The original data are assigned phases for each, then re-ordered in ascending sequence. The re-ordered data are examined by inspecting them across the full phase interval between zero and one. For each trial period, the sum of the lengths of line segments joining successive points (the string-lengths) are calculated (Lafler & Kinman 1965). In the plot of the string-length versus the trial period, the minima can be considered to correspond to the underlying period. The methods are especially useful for a very small number of randomly spaced observations (Renson 1978).

The Fourier transform connects the time and frequency domains (Bloomfield 1976). Normally, the power spectrum of a time series, which is the square of the amplitude of each harmonic, is used as a diagnostic tool. This provides each harmonic’s contribution to the time series’s total energy.

We used the Lomb–Scargle (LS) algorithm (Zechmeister & Kürster 2009) because it also includes a FAP estimation (VanderPlas 2018). The method is a variation of the discrete Fourier transform (DFT), in which an unevenly spaced time series is decomposed into a linear combination of sinusoidal and cosinusoidal functions. The data are transformed from the time to the frequency domain (LSP), which is invariant to time shifts. From a statistical point of view, the resulting periodogram is related to the $\chi^2$ for a least-squares fit of a single sinusoid to data, which can treat heteroscedastic measurement uncertainties (Lomb 1976; Scargle 1982).

To define whether a time series includes a periodic signal (or not), we followed the statistical approach published by Balués (2008). The FAP measures the probability that a data set with no signal would lead to a peak of a similar magnitude. Previously Scargle (1982) had already estimated the cumulative

![Figure 2](https://example.com/figure2.png)

Figure 2. Light curve of the star KIC 1293468 ($V = 15.545$ mag) observed by Kepler. The red and black dots show the PDCSAP and SAP fluxes, respectively. Note: the upper panel only shows two-quarters of the full data set, while the middle panel shows the offsets of the different quarters and the lower panel shows the final cleaned light curve in magnitudes.
Table 1. Essential data for our sample stars, sorted by increasing right ascension.

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Notes. The columns denote: (1) KIC ID; (2) right ascension (J2000); (3); (4) \( T_{\text{eff}} \) from Berger et al. (2020); (5) \( \log g \) from Berger et al. (2020); (6) zero point (HJD) of the light curve; (7) standard deviation of the mean of the light curve; (8) logarithmic false-alarm probability for the frequency range below 0.1 c/d; (9) logarithmic false-alarm probability for the frequency range 0.1 to 2.0 c/d; (10) logarithmic false-alarm probability for the frequency range 2.0 to 25.0 c/d.

In general, non-variability is challenging to define, as the final ‘constancy level’ of a time series depends on: (1) the frequency range, namely: the time series can behave differently in the low- and high-frequency domain; (2) the time basis of the observations: the spectral window function of the Fourier transform depends on the time basis and gaps of the data; (3) amplitude-noise level: the significance of a detected amplitude depends on the noise level of the corresponding frequency domain; (4) the wavelength region-filter: it is known that the amplitude of variability can depend on the wavelength (see more on classical pulsating variables); (5) applied ‘pipeline software’: it is important to know whether the pre-reduction steps include smoothing in certain frequency domains, such as a low-passband filter; (6) applied ‘cleaning software’: removing possible outliers can significantly alter the detection of significant peaks in the amplitude spectrum; and (7) finally, the applied time series analysis method: different methods are specially developed to detect certain features in the light curve, like transients or flares.

In the case of the Kepler mission, this would mean that starting from the SAP data sets, depending on which software and algorithm are used, it is possible to arrive at very different results about a star’s non-variability. It is therefore very important to clearly describe each consecutive step of the working flow. In Sects. 4 and 5, we present the data preparation procedure and the applied time series analysis method. Below, we describe the definition of non-variability we applied for the final data sets.

The general characteristics of the Kepler data sets are extensively described in Murphy (2012). Let us recall that the time basis is three and a half years. For the LC data, there are especially two problematic frequency regions, at very low frequencies and close to the Nyquist frequency (equal to half the sampling frequency of the light curve, i.e. 25 c/d). The latter is not important for our analysis because it only affects variability at even higher frequencies. Those frequencies are mirrored and misidentified in the domain close to 25 c/d, respectively.

As Murphy (2012) pointed out, peaks detected in the low-frequency domain (up to 0.5 c/d) can result from long time-scale processes such as differential velocity aberration, with stars moving across the CCD, or the changing amount of background contamination light. Also, CCD degradation due to high-energy cosmic ray impacts could, for example, cause such effects. Therefore, the frequency spectrum needs to be interpreted with care.

Based on the instrumental characteristics and the known periods of variable stars (Percy 2007), we chose three different...
Fig. 3. Examples of different stages of calculated FAPs. The LSPs of the stars KIC 1870375 (log FAP = $-45/-2/-1$), KIC 2157526 ($-21/-2/-0$), KIC 1576739 ($-8/-0/0$) and KIC 3751287 ($-2/-1/0$). Note: absolute values of the power differ.
7. Results and conclusions

As described in Sect. 3, we performed a cleaning process and time series analysis of the light curves for 138 451 stars. According to the limits for non-variability (listed in Sect. 6), we defined two samples:

- Sample 1: due to the discussed possible instrumental effects in the low frequency domain, this sample consists of 13 211 stars with \( \log \text{FAP} \geq -2 \) in the other two domains (0.1 to 25.0 c/d).
- Sample 2: this stricter set comprises of 943 stars for which \( \log \text{FAP} \geq -2 \) is true for all three frequency domains.

In Fig. 3, we show four examples of LSPs with different \( \log \text{FAP} \) values. It clearly shows how difficult it is to interpret the FAPs in the low frequency domain. It is therefore essential to also take the standard deviation of the whole data set and the noise level in the corresponding frequency domain into account.

If we analyse the histogram of the standard deviation of the mean (Fig. 4), we find the peak of the (assumed Gaussian) distribution at 0.520 ± 0.002 mmag and a full width at half maximum (FWHM) of 0.411 ± 0.004 mmag. Here, we see the effects of the photon noise and the actual observed time basis (number of quarters), namely, the time sampling. It is not immediately possible to transform the noise of the light curve into the noise in the corresponding LSP (VanderPlas 2018). Therefore, the user is advised to inspect the data sets manually.

We recall that we searched for a periodic signal in the data sets. Therefore, the applied methods can mainly detect classical pulsation, eclipses, and so on. Single events such as flares and transits might still be found for stars in our sample.

The catalogue with all essential information will be provided in electronic form in VizieR (CDS). We also set up the project NONVstAR webpage. It includes all light curves and the calculated LSPs. All the corresponding data can be downloaded from there.

Finally, we investigated the location of the stars of both final samples in the HRD as shown in Fig. 5. Only a handful of stars are hotter than 7000 K. Otherwise, all evolutionary stages up to the red giant branch (RGB) are well populated. This region exhibits several very different variability classes (Eyer & Mowlavi 2008).

The presented light curves of apparent non-variable stars from the Kepler satellite mission are still the most accurate found to date. The applied workflow could easily be adapted to any other datasets, such as those from the Transiting Exoplanet Survey Satellite (TESS, Antoci et al. 2019) mission. As more and more photometric light curves over longer timespans become available, it will be interesting to investigate which astrophysical parameters are distinguishable among variable and non-variable stars in the same location on the HRD.

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\[ \log \text{FAP} \]

Fig. 4. The histogram of the standard deviation of the mean for the combined Samples 1 and 2, respectively.

Fig. 5. \( \log g \) versus \( T_{\text{eff}} \) diagram for sample 1 (upper panel) and sample 2 (lower panel). The astrophysical parameters were taken from Berger et al. (2020).

frequency domains for which we calculated the LSPs and the FAPs for the highest peak. These are Domain 1 – below 0.1 c/d; Domain 2 – 0.1 to 2.0 c/d; Domain 3 – 2.0 to 25.0 c/d.

The first domain includes the most severe instrumentally induced frequencies. We note that the Kepler satellite was in an Earth-trailing orbit with a period of 372.5 days. The second and third regions include rotationally induced variability and classical pulsators.

Finally, we had to define when to consider a light curve not included as periodical signal for a given amplitude (or noise level). Using the results from the literature for (in particular) low-amplitude variables of different spectral types (Corsaro et al. 2013; Bowman et al. 2016; Giles et al. 2017; Vrard et al. 2018; Hümmerich et al. 2018), we decided to use a value (limit) of \( \log \text{FAP} \geq -2 \) for our subsequent analysis.

In addition to the described time series analysis, we calculated the standard deviation of the mean for each final light curve. This provides a valuable parameter for the data’s noise level. Table 1 lists the essential data for our sample stars (note: full table is only available in electronic form).
References

Torres, G. 2010, AJ, 140, 1158