Manuscript version: Author’s Accepted Manuscript
The version presented in WRAP is the author’s accepted manuscript and may differ from the published version or Version of Record.

Persistent WRAP URL:
http://wrap.warwick.ac.uk/179624

How to cite:
The repository item page linked to above, will contain details on accessing citation guidance from the publisher.

Copyright and reuse:
The Warwick Research Archive Portal (WRAP) makes this work of researchers of the University of Warwick available open access under the following conditions.

This article is made available under the Creative Commons Attribution 4.0 International license (CC BY 4.0) and may be reused according to the conditions of the license. For more details see: http://creativecommons.org/licenses/by/4.0/.

Publisher’s statement:
Please refer to the repository item page, publisher’s statement section, for further information.

For more information, please contact the WRAP Team at: wrap@warwick.ac.uk
Automated analysis of oscillations in coronal bright points

B. Ramsey$^{1,2}$, E. Verwichte$^2$, and H. Morgan$^1$

$^1$ Aberystwyth University, Ceredigion, Cymru, SY23 3BZ, UK e-mail: brr24@aber.ac.uk
$^2$ Centre for Fusion, Space and Astrophysics, Department of Physics, University of Warwick, Coventry CV4 7AL, UK e-mail: erwin.verwichte@warwick.ac.uk

Received date / Accepted date

ABSTRACT

Context. Coronal Bright points (BP) are numerous, bright, and small-scale dynamical features found in the solar corona. BPs have been observed to exhibit intensity oscillations across a wide range of periodicities and are likely to be an important signature of plasma heating and/or transport mechanisms.

Aims. We present a novel and efficient wavelet-based method that automatically detects and tracks the intensity evolution of bright points using images from the Atmospheric Imaging Assembly (AIA) on board the Solar Dynamics Observatory (SDO) in the 193Å bandpass. Through the study of large, statistically significant set of bright points we attempt to place constraints on the underlying physical mechanisms.

Methods. A Continuous wavelet transform (CWT) in 2D is used to detect the BPs within images. 1D CWTs are used to analyse the individual BP time series to detect significant periodicities.

Results. We find significant periodicity at 4, 8-10 minutes, 17, 28 and 65 minutes. BP lifetimes are shown to follow a power-law with exponent $-1.13 \pm 0.07$, the relationship between BP lifetime and maximum diameter similarly follows a power-law with exponent $0.129 \pm 0.011$.

Conclusions. A wavelet based method is successful at detecting and extracting BPs in addition to an analysis of their intensity oscillations. Future work will expand these methods into larger data sets, and more generally into multi-instrument, simultaneous observations.

Key words. Sun: corona - Sun: oscillations - Sun: atmosphere

1. Introduction

Coronal bright points (BPs) are ubiquitous forms of activity seen as areas of point-like emission in EUV to X-ray wavelengths, in both quiet-Sun and coronal hole regions of the solar corona (Madjarska 2019). They have been the subject of intense interest since their discovery in the 1970s (Vaiana et al. 1973; Sheeley & Golub 1979). A BP is a collection of small coronal loops (a mini active region) that forms an area of diffuse emission 10-60 arcsec in size with a bright core of about 5 to 10 arcsec (Golub et al. 1977; Hirzberger et al. 2008). BPs are associated with small magnetic bipolar regions with typical photospheric magnetic fluxes of $10^{-15} - 10^{-20}$ Mx (Golub et al. 1976).

On average there are 400-800 BPs per day on the solar disk (Sattarov et al. 2002; McIntosh & Gurman 2005; Alipour & Safari 2015). The BP frequency outside the active region belt does not show much variation with the solar cycle, though the number decreases with temperature as the BP production rate operates at temperatures well below the temperatures operated by soft X-ray detectors (Hara & Nakakubo-Morimoto 2003; McIntosh & Gurman 2005). The lifetimes of BPs seen in X-ray are found to exhibit a statistical distribution, with a mean value of around 2 hours (Golub et al. 1974) (Alipour & Safari 2015) showed that BP size follows approximately a power-law distribution with exponent 0.14 with respect to the lifetime. Bright coronal features with smaller scales, around 4 Mm, and lifetimes less than 1 hour are observed. These features are more commonly known as brightenings, or transient coronal brightenings, (Chen et al. 2021; Berghmans et al. 2021) and are not considered BPs in this work.

BPs have been observed to host intensity oscillations in both X-ray and EUV with a broad range of periodicities from a few minutes to hours (Sheeley & Golub 1979; Christensen-Dalsgaard & Frandsen 1983; Strong et al. 1992; Ugar-Teira et al. 2004; Kariyappa & Varghese 2008; Tian et al. 2008; Kumar et al. 2011; Chandrashekar et al. 2013). Early observations by Sheeley & Golub (1979) showed morphological evolution of about 6 minutes. Long period oscillations from between 8 and 64 minutes have been observed by Tian et al. (2008). Longer period oscillations have also been found by Kariyappa & Varghese (2008) in X-ray BPs as seen in Hinode using power spectra analysis, with periods between 9 and 133 minutes. Wavelet analysis of time series by Ugarte-Urra et al. (2004) showed BP oscillation periods as short as 236 seconds, with dominant periodicities at 8 and 13 minutes. It is unknown if these oscillations are a result of propagating magneto-acoustic waves, or recurrent magnetic reconnection.

In addition to intensity oscillations, there have also been decayless kink oscillations seen in BPs. These physical oscillations have been seen with periods between 1 and 8 minutes with an average of 5 (Gao et al. 2022).

Other than within BPs, intensity oscillations have been observed in other coronal structures. Longer period oscillations of 8-27 hours have been detected in coronal filaments (Foulon, C. et al. 2004). More recent studies by Auchère et al. (2014) showed long period intensity oscillations of 3 to 16 hours. These oscillations...
2. Automated analysis procedure

2.1. Data Acquisition

We focus on the analysis of imaging data from AIA in the 193Å channel that covers the Fe XII and Fe XXIV emission lines and is sensitive to temperatures around 1.5 and 20MK. It is chosen as a compromise between detecting many small-scale features such as loop foot points in lower temperature bands and the hottest BPs in the hotter band passes, whilst maintaining a good signal to noise ratio. For this study, imaging data from three days from 01 Jan 2020 to 03 Jan 2020 inclusive are used at the full time cadence of 12s. Level1 data was used, that is, images have CCD read noise removed and rotated so as to align with solar north. The images have a pixel size of 0.6 arcsec.

To find a suitable medium between image detail and processing time during the detection phase, images are reduced in resolution by a factor 4, from 4096 × 4096 to 1024 × 1024, using linear interpolation. The first image in a time sequence is used as the initial reference image, and the pointing of all subsequent images are aligned to it. This reduces offsets and helps keep BPs centred within sub-images during tracking. Consistent image headers have been maintained. The near and off-limb areas of the image are excluded from the region of interest (ROI) by use of a circular image mask centred on the solar disk and with a radius equivalent to 0.7 R⊙.

For the automated detection of BPs in the images, we apply a two-dimensional continuous wavelet transform (CWT) to the imaging data (Antoine et al. 2002; Hochedez et al. 2002; De Pontieu et al. 2005; Mallat 2008; White et al. 2012). The CWT of a two-dimensional image, I(r), is defined as

\[
\text{CWT}(I)(b, a, \theta) = \frac{1}{a^d} \int_{-\infty}^{\infty} I(r) \psi \left( \frac{1}{a} R_{\theta,\phi} (r - b) \right) d^2r, \tag{1}
\]

where \(\psi(r)\) is called the mother wavelet. In the transform it is translated by a 2D displacement parameter \(b\), scaled by the finite scale parameter \(a\), and rotated through the rotation matrix \(R_{\theta,\phi}\) at an angle \(\theta\) (Wang & Lu 2010). The transform can be defined depending on the chosen norm, which is expressed through the index \(n\). For the typical L₁ norm \(n=2\), which we will use throughout this paper. In an L₁ norm magnitudes of vectors are calculated as the sum of the absolute values of their complex components. The CWT corresponds to a scale-space convolution of an image with a mother wavelet.

\(\psi(r)\) is a wavelet if it has the property that it is localised both in space and in its reciprocal space, that is, \(\int |\psi(r)|^2 \, dr = 0\), and that it fulfills the admissibility condition in reciprocal space \(\int |\hat{\psi}(k)|^2 \, |k|^2 < 0\), where \(\hat{\psi}\) and \(k\) are the Fourier-transform of \(\psi\) and the 2d wave vector, respectively. The Mexican Hat wavelet, which is proportional to the Laplacian of a 2D Gaussian profile satisfies these conditions:

\[
|\psi(r)| = -\nabla^2 \exp \left( -\frac{|r|^2}{2} \right) = (2 - |r|^2) \exp \left( -\frac{|r|^2}{2} \right). \tag{2}
\]

The Mexican hat wavelet is isotropic so that the transform is independent of rotation angle \(\theta\). To understand how this 2D CWT may be employed for the detection of BPs, we calculate the
transform of a 2D Gaussian profile \( I(r) = A \exp\left(-\frac{(r-c)^2}{2\sigma_0^2}\right) \) with amplitude \( A \), with \( \sigma_0 \) and centred on position \( c \):

\[
\text{CWT}(I)(b, a) = \frac{1}{a^2} \int_{-\infty}^{\infty} A \exp\left(-\frac{(r-c)^2}{2\sigma_0^2}\right) \psi\left(\frac{r-b}{a}\right) \, d^2r ,
\]

\[
= \frac{2\pi A}{\left(1 + \frac{a^2}{(c^2)}\right)^2} \psi\left(\frac{b-c}{\sqrt{a^2 + \sigma_0^2}}\right) .
\]  

The result is a Mexican Hat wavelet located at \( c \) with a width and amplitude that depend explicitly on scale \( a \) (illustrated in Fig. 1). The transform is maximal at \( b = c \). At that position, the transform has a clear profile as a function of \( a \) with a maximum value of \( \pi a \) at \( a = \sigma_0 \). For scales smaller or larger than \( \sigma_0 \), the transform drops away sharply. This is illustrated in Fig. 2. Therefore, this wavelet can be used to differentiate point-like features across scales. Furthermore, the Mexican Hat CWT of a constant or linear trend in intensity is zero due to its characteristic as a Laplacian, that is, \( \text{CWT}(Axy + Bx + Cy + D) = 0 \). With the removal of background signals, the CWT enhances image contrast.

All these characteristics make this wavelet particularly well-suited for the detection of point-like intensity features in solar images.

The CWT is applied in two stages, illustrated in Fig. 3. First, we apply a simple circular mask to the image with a diameter 1% less that of the sun. This obscures the bright limb detail. Then we perform a 2D CWT on that image with a scale of approximately \( 90 \) arcsec. This scale is much larger than the typical BP, and on the order of active regions. Therefore, regions of large CWT intensity at that scale correspond to active regions. As it is easy for an automated algorithm to confuse BPs and the foot points of active region loops, we exclude active regions from the ROI by subtracting the detected regions from the image mask. An active region is designated where the intensity of the real part of the CWT is greater than the 97th percentile of the intensity. A mask of the above defined area is applied.

Secondly, a 2D CWT is performed on the image with the active regions and limb removed. Another simple circular mask is applied with a diameter of 70% of the sun-disk radius. This will prevent detections close to the limb that may be affected by the line of sight (LOS) reduction and geometric projection. This will mean BPs close to the 0.7R_⊙ boundary to appear approximately 30% smaller than at disk centre. The 2D CWT is applied at the scale of \( \sigma_0 = 7 \) arcsec, the typical scale of BPs (Golub et al. 1977; Hirzberger et al. 2008). Candidate BPs are initially detected within the second circular mask as regions at the 99th percentile of the real part of the CWT.

2.3. BP tracking

For each candidate BP ROI, its properties such as location, total intensity, semi-minor and semi-major radii, elliptical shape and orientation are extracted. First, we use this to further eliminate false detections. Regions with an eccentricity greater than 0.6 are removed from the ROI, thereby eliminating likely elongated loop structures and other structures that do not fit the general morphological shape of a BP, although this does not prevent a candidate BP from changing shape over its lifetime. Furthermore, regions with total pixel areas of less than 30 arcsec^2, are also removed as potential short-lived, small-scale solar transients or cosmic rays. The above selection steps reduce the number of detections by about 50%. We call the remainder of the detections simply BPs.

In order to ascertain the time range over which a BP is visible, a detection procedure is repeated at 1 hour time intervals. At each hour the found BPs are compared with those found an hour earlier. This is to determine newly formed BPs over those pre-existing, and is achieved in the following way. A binary image of the current image’s detections is subtracted from a binary image of the previous image’s detections. This creates a third image with the following characteristics. Newly formed BPs will be designated with a value of -1 and pre-existing BPs will have a value of 0, and BPs which disappear will have a value of 1. We can use these values to extract the newly formed BPs, for which we can use the average position coordinates to generate a sub-image centred on BP, with a size approximately 8 times larger than the size of the detected BP at its birth hour in pixels. This was determined as a compromise between computational expense of an unnecessarily large sub-image, and the maximum size of a BP in literature (Golub et al. 1977; Mandias 2019) approximately 60 arcsec. This sub-image sizing will allow the BP...
Fig. 3. a): Full disk AIA 193Å on 2020/01/01 at 01:00:05 UT. b): 2D CWT at the active region scale $d_{AR}$. The active region is detected by applying a threshold value at the 97th percentile of the CWT value. This threshold area is the area within the red contour. c): 2D CWT at the BP scale $d_{BP}$. The active region is masked by removing the area denoted by the red contour, as in image b. The larger black circle is applied at 0.7 $R_\odot$, obscuring limb, off limb, and edge effects. In this case the AR mask is outside the limb mask. d): Full disk AIA 193Å on 2020/01/01 at 01:00:05 UT. Candidate BPs shown as white crosses. Masked areas denoted by red/black contours.

Fig. 4. a): AIA 193Å example BP #149 on 2020/01/01 at 01:59:59 UT. b): Application of a CWT at scale $d_{BP}$. White crosses highlight the maxima in the CWT which exceed the threshold value after the application of a 2D weighted Gaussian to the CWT image, the red cross highlights the maxima closest to the centre of the image.

to grow over its lifetime, and remain within the sub-image. The corresponding heliographic coordinates are then used to track the BP position with time by rotating them according to the local synodic solar differential rotation rate.

We then use a detection procedure and similarity test to determine the last image in which a BP exists. This works as follows. The 2D CWT is applied to the first sub-image at a scale length of 7 arcsecs. As with the initial detection, a threshold mask is applied to the CWT image, initially at the 95th percentile. If more than 1 area is detected within the CWT image, the process is repeated in increasing 0.01% percentile increments until only 1 area remains. This area should be the brightest point of the BP sub-image but it might not be in the centre of the sub-image, therefore the sub-image is re-centred on this point and the CWT re-applied. This process is then repeated on the sub-image 1 hour later, using the coordinates of the re-centred BP.

Two tests are performed in order to determine if there is a BP present in a sub-image. First, we find the difference between the CWT value at the centre of the real CWT image and the minimum CWT value in the image, if this value is small, less than 100, then the CWT value at the centre and the minimum are close together, therefore a BP is unlikely to be in the centre of that image. Next, the centre value of the new BP sub-image and the standard deviation of the average of the previous and current BP sub-image are found. If the quotient of these two numbers is greater than 5 and the first criteria is also met then a BP is said to exist. If either of these conditions are not met, then the BP has disappeared and we take the last known image containing a BP as the BPs death hour. This death hour is further refined during the tracking process.

The birth hours are determined during the detection and comparison with previous images. The birth hours for the BPs detected in the first image of the full data set are not known as they lie outside the bounds of the data set, and are eliminated from the statistics. With birth and death hours established, we create for each BP a 3D data cube from the 193Å dataset, at the full spatial and temporal resolution (0.6 arcsec per pixel and 12s), of a restricted field of view of between $72x72$ and $115x115$ arcsec, at the heliographic rotating coordinates centred on the BP.

2.4. BP morphology

For each BP and at each time step, we extract the relevant morphological characteristics. To achieve this, we need to identify...
more closely which portion of the sub-image is identified as being part of the BP. We apply again the 2D CWT to the image with a scale $\sigma=7$ arcsecs. We then further weight the CWT signal by multiplying it with a 2D Gaussian with unity amplitude centred on the field of view. We then identify the BP maximum as the maximum in the image that is within the 95th percentile of the total maximum, and closest to the centre of the field of view (see Fig. 4). The 2D Gaussian weight is then centred on the location of the found BP maximum. The BP itself is then detected as the region overlapping the maximum and that exceeds the sub-image median by 6$\sigma$. The region is represented by a binary mask. This region is grown to encompass all neighbouring pixels down to 3$\sigma$. Any remaining holes in the found region are closed using morphological filtering. This BP extraction method is illustrated in Fig. 5. From the binary mask and original 193 Å sub-image, statistical properties can then be extracted for the BP such as average and maximum intensity, size and shape. By repeating this procedure for all time steps, time series of BP properties are created.

### 2.5. BP time series analysis

The method of extracting a BP from the background, as defined in section 2.4, may not successfully detect and extract the BP across the whole time series. In order to prepare the morphological statistics of the BPs, some further processing steps must be considered. In these instances two actions are performed on the morphological data prior to extracting statistical results. First, instances in the time series are found wherein a BP is not extracted consecutively for 8 images; this is approximately 96 seconds and is about half the period of the frequently observed 3-minute oscillations. Any instances of missing data which last for longer than or equal to 8 images removes potentially important data, therefore the time series are cut off at the beginning of the gap. The remaining gaps in the data, less than 8 images, are then filled in using linear interpolation. Second, if the number of remaining gaps equates to more than 15% of the number of data points, the whole time series is discarded. This removes the statistical unreliability that comes with interpolating too many gaps in a data set. Additionally any BP time series which has nonphysical values such as negative intensity, or zero-valued area are dismissed. Some time series show discontinuity in the form of intensity jumps, which will result in the 1D CWT (Torrence & Compo 1998) power being dominated by the discontinuous jumps if present, therefore before these time series are analysed, a point-filter is applied to smooth sporadic jumps. The point-filter identifies outliers by comparing values to the local standard deviation, and replaces the value by a new value closer to local mean. Lastly, each time-series is manually checked to ensure that any anomalous time-series are not included in the results analysis. Each time-series of average BP intensity is analysed using a 1D CWT using a custom noise model given by Auchère et al. (2016) in the form $\sigma(y) = A\nu^\beta + BK_\nu(y) + C$, whereby the first term represents the power-law dependency given by background stochastic fluctuations. The second term is a kappa function which related to pulses in the time series. The final term corresponds to high-frequency white noise.

### 3. Results & Discussion

The detection method found 3308 BPs across the time period used, 1191 found on 2020/01/01, 1141 on 2020/01/02 and 976 on 2020/01/03, with the number of BPs used in the analysis reduced to 656.

#### 3.1. General BP Characteristics

Figure 6 shows the distribution of BP lifetimes, with a mean lifetime of 6.8 hours and a range from 1 hour to 22 hours. We have fitted a power-law of the form $y = ax^\beta$ with an exponent equal to $-1.13 \pm 0.05$. The lifetime shows an almost power law distribution across all lifetimes, with a good fit up to approximately 700 minutes, after which the function begins to diverge. Previous work by McIntosh & Gurman (2005) found a power-law behaviour with exponentials at longer lifetimes. The exponents for the power-law by McIntosh & Gurman (2005) vary with temper-
The average BP diameter was obtained by taking twice the mean semi-major radius for each BP across its lifetime. Similarly, the maximum BP diameter is defined as twice the maximum semi-major radius that a BP achieves across its lifetime. The mean diameter is $24.06 \pm 0.19$ arcsec, with a normal distribution of width $\sigma = 4.93 \pm 0.19$, and a range from 10 arcsec to 39 arcsec, as shown in Fig. 7. When we compare mean diameter against a BP’s lifetime, we find no clear relationship. However, there is a relationship between the maximum diameter and lifetime, as shown in Fig. 8. The distribution in this figure shows a general increase in the diameter with lifetime. We bin the lifetimes at one hour increments, and calculate the mean and standard deviation of maximum diameters for each bin. These are shown as the white circles (means) and blue error bars (standard deviations) in Fig. 8. These show an increase from the shortest to longest lifetimes. At the very longest lifetimes we see a decrease in the average maximum diameter, but there are only a few BPs at these long lifetimes, so the statistics are not reliable. To further characterise this relationship, we fit the maximum diameters to a power law of the lifetimes. Note that this fit is done with all the individual BP data, and not to the bin averages. Our power-law fit has the form $D_{\text{max}} = \alpha \tau^\beta$.

$$D_{\text{max}} = (7.72 \pm 0.87) \tau^{0.129 \pm 0.011},$$

where $D_{\text{max}}$ and $\tau$ are the maximum BP diameter in megameters and lifetime in seconds, respectively. The parameter errors here are obtained as the standard deviation of the non-linear least mean square fitting method used to fit the data, with an RMS error of 0.07. This power law confirms the clear relationship between maximum diameter and lifetime. That there is no clear relationship between mean diameter and lifetime is surprising, particularly given the relationship shown by figure 11 of Alipour & Safari (2015). Their study, however, looks at considerably smaller lifetime and spatial scales than ours. The lack of a relationship between lifetime and mean diameter, and the clear relationship between lifetime and maximum diameter is interesting, and requires further study. Our detection method does have a bias, in that we discard BPs with some minimum diameter ($6.2''$) and minimum lifetime (1 hour). Furthermore, at long lifetimes we have far fewer BPs. A larger study would help with the statistics at longer lifetimes.

### 3.2. Example BPs

Showing here BP #149, #195, #685, #735, #840, and #1378 as examples, we can apply 1D CWTs to the average BP intensity.
Fig. 10. Top to bottom: BP #195, #685, #735, #840 and BP #1375. The left panels show the average BP intensity time series, with the wavelet power below. The right panels show the Fourier spectrum in grey, the global wavelet power spectrum in black. The solid red and orange lines show the global and local wavelet significance levels respectively. The noise model components are shown as follows; power-law in orange-dash, the kappa function is in blue-dash, and the white noise is shown in green-dash.
Fig. 11. Left most panel shows the AIA 193Å image at the beginning of the time range of interest. The remaining three panels shows images at three times separated by 2 minutes. At each pixel the time series has been bandpass-filtered around the period of 4 minutes with a Hann filter with a typical width equal to the mode frequency.

Fig. 12. Left most panel shows the AIA 193Å image at the beginning of the time range of interest. The remaining three panels shows images at three times separated by 4 minutes. At each pixel the time series has been bandpass-filtered around the period of 8 minutes with a Hann filter with a typical width equal to the mode frequency.

Fig. 13. Left most panel shows the AIA 193Å image at the beginning of the time range of interest. The remaining three panels shows images at three times separated by 8 minutes. At each pixel the time series has been bandpass-filtered around the period of 16 minutes with a Hann filter with a typical width equal to the mode frequency.

We can see from the bottom-left panel of this figure, several periodicities with significant power appearing regularly across the lifetime of the BP, namely at periods between 1 and 10 minutes. We can see from the right panel of Fig. 9 a highly structured Fourier spectrum in grey, with the wavelet power shown in black. We can see regions of wavelet power above the significance levels, these regions are more concentrated at the beginning of the BPs lifetime, especially at shorter periods.

The global and local significance levels are denoted in Fig. 9 as the solid red and orange lines respectively. The global significance level represents the wavelet power that lies above a global confidence level when compared with the noise model. The local significance level represents the probability that power in a single bin is significant when compared to the noise model. Auchère et al. (2016) provide a detailed explanation of the noise model and accompanying significance levels.

At shorter periods, between 1 and 10 minutes, the wavelet power is above both the local and global significance levels.
whereas at longer periods, at approximately 30 and 70 minutes, the wavelet power is only above the local significance level.

We can see further examples of these wavelet power spectra in Fig. 10. Here we show the wavelet spectra and powers for BPs #195, #685, #735, #840, and #1378. These BPs show a range of lifetimes, from 2 to over 16 hours. We can see from these BPs some common periodicities, e.g., for BPs #685, and #735, fairly distinct peaks in both the Fourier and wavelet power spectra which lie above the local and global significance level, at approximately 4 minutes. While BP #840 has a suggestion of periodicity at 4 minutes above the local significance only. At longer periods we can start to see some common periodicity in BPs #195, #685, and #735, at approximately 30-40 minutes.

The periods of interest seen in Fig. 9 can be visualised for BP #149 in Figs. 11, 12 & 13. We choose to look at periods of 4, 8, and 16 minutes as these are periods which can be seen in the main wavelet plot as areas above the significance level. We apply a temporal bandpass filter around the period of interest with a Hann filter with a typical width equal to the mode frequency. This shows a change over the oscillation cycle, with the spatial structure of the three oscillation periods showing clear differences. For the 4-min oscillation in Fig. 11 the BP shows the suggestion of anti-phase behaviour between its two sides which could be an m=1 mode. Such modes have also been observed in sunspots (Jess et al. 2017) and chromospheric vortices (Murabito et al. 2020). However, the structure of a BP is significantly different from that of a sunspot or chromospheric vortex, but could be a suggestion of leaky p modes about the eastern/western sides which would constitute an apparent m=1 mode structure. The 8 and 16 mins oscillations show a phase coherence that maps out the coronal loops in the BP. The acoustic cut-off frequency in the quiet-Sun vary in the range of 4-6 mHz (3-4 minutes) (Felipe & Sangeetha 2020). Intensity oscillations with similar or shorter periods are interpreted to be acoustic in nature. Those with periods substantially longer, 10 minutes and more, are unlikely to be acoustic waves propagating up from below and instead they may be evanescent acoustic tails or are associated with thermal limit cycles (e.g. Foullon, C. et al. (2004); Auchère et al. (2014); Froment et al. (2017); Verwichte & Kohutova (2017)).

### 3.3. General Periodicity

There are, more generally, many periodicities potentially detected across all of the analysed BPs. To better visualise the significance of the detected periodicities we take the significant normalised wavelet power, i.e. the power within the cone of influence (COI) and within the white contours of Fig. 8 as an example, which lasts for at least 3 complete periods. These are then summed together for all BPs, and normalised. All BPs can contain periodicity less than 1 hour, conversely, periodicity greater than 1 hour cannot be within BPs with lifetimes less than that period. We therefore apply a weighting to the total normalised power. This result can be seen in Fig. 14. In black we have the normalised and weighted total significant power for BPs with lifetimes greater than 1 hour. In blue are the BPs with lifetimes of 1 hour. Combining these results in a discontinuity at 10 minutes as this is the longest periodicity that the wavelet can detect, period greater than 10 minutes fall outside the COI for BPs with lifetimes of 1 hour.

We can see from these two plots a peak below and above 4 minutes (average time, 4.11 minutes). For BPs of 1 hour we see another peak between 8 and 9 minutes, whereas for the remaining BPs we see this peak at 10 minutes. There is a final noticeable peak at approximately 17 minutes. For longer periodicity, there are slight humps within the plot at approximately 28, 40, and 49 minutes. We can see at longer period, the suggestion of additional periodicity at approximately 65 to 75 minutes. 

Ugarte-Urra et al. (2004) showed dominant periods of between 8 and 13 minutes in BP oscillations. Our 10-minute peak falls within this range, with the physical nature still uncertain.
but could be evanescent acoustic modes through the transition regions resonant in loops or thermal-limit cycles (Habbal & Withbroe 1981; Verwichte & Kohutova 2017). The peaks at 17 and 28 and 65 minutes seen here, have been seen by Tian et al. (2008) (16, 28, & 64 minutes). We do not see a clear peak at 32 minutes as was noted by Tian et al. (2008), however this potential peak in our case could be too broad and not discernable in Fig. 1. Zhang et al. (2012) found periodicity of about 1 hour, suggesting them to be quasi-periodic recurrent flashes. The peak at 17 minutes falls within the range of 15 - 25 minutes seen by Chandrashekhar & Sarkar (2015) within their simulated loop and nanoflare model, in addition to the observed values by Christensen-Dalsgaard, J. & Frandsen, S., 1983, ApJ, 82, 165

The aim of this work was to analyse a large set of coronal bright points using continuous wavelet transforms in 2D and 1D. We present a novel method for the detection and tracking of BPs using 2D CWTs. We analyse the morphology of these BPs, and investigate intensity oscillations using 1D CWTs.

We find that BPs have a lifetime distribution that follows a power-law, with exponent $-1.13 \pm 0.07$. We find that the relationship between a BP’s lifetime and maximum diameter roughly follows a power law with exponent $0.129 \pm 0.011$. These statistical results compare well with previous studies of BPs (Alipour & Safari 2015; McIntosh & Gurman 2005). The analysis of intensity oscillations within BPs shows a broad range of significant periodicity between 1 and 100 minutes, with notable peaks at 4, 10, and 17 minutes, and the suggestion of peaks at longer periods, namely 28 and 65 minutes. Further, in-depth analysis is required to study the spatial mode structure of these oscillations to allow for constraints on their physical nature.

There is a clear relationship between a BPs area and intensity, however the effects of limb projection are not considered and future work will endeavour to address this. The hope is the automated methods described here will allow for a much larger statistical study of BP intensity oscillations and their morphological characteristics in the future. Additionally, further work will endeavour to expand the automated methods into different SDO/AIA passbands and different instruments.

Acknowledgements. The wavelet transform has been performed using the Python wavelet module by Erwin Verwichte (University of Warwick) and was supported by a UK STFC grant ST/L006324/1. We acknowledge STFC studentship ST/V506527/1, and STFC grant ST/S000518/1 to Aberystwyth University.

Kumar, M., Srivastava, A. K., & Dwivedi, B. N. 2011, MNras, 415, 1419
Madjarsova, M. S. 2019, Living Reviews in Solar Physics, 16, 2
McIntosh, S. W. & Gurman, J. B. 2005, Sol. Phys., 228, 265
Wang, N. & Lu, C. 2010, Journal of Atmospheric and Oceanic Technology, 27, 652

References

Article number, page 10 of 10