A Global Survey of EUV Coronal Power Spectra

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Abstract We present results of an investigation of single-pixel intensity power spectra from a 12-hour time period on 26 June, 2013 in a 1600x1600-pixel region from four wavelength channels of NASA’s Solar Dynamics Observatory Atmospheric Imaging Assembly. We extract single-pixel time series from derotated image sequences, fit two models as a function of frequency, ν, to their computed power spectra, and study the spatial dependence of the model parameters: (1) a 3-parameter power-law + tail, \( A\nu^{-n} + C \), and (2) a power-law + tail + 3-parameter localized Lorentzian, \( A\nu^{-n} + C + \alpha/(1 + (\ln(\nu) - \beta)^2)^{\delta^2} \), to model periodicity. Spectra are well-described by at least one of these models for all pixel locations, with average data/model correlations of 0.93 and standard deviation of 0.06. The spatial distribution of best-fit model parameters are shown to provide new and unique insights into turbulent, quiescent and periodic features in the EUV corona and upper photosphere. Findings include: individual model parameters correspond clearly and directly to visible solar features; detection of numerous quasi-periodic 3- and 5-minute oscillations; observational identification of concentrated magnetic flux as regions of largest power-law indices \( n \); identification of sporadically located 5-minute oscillations throughout the corona; detection of the known global \( \sim 4.0 \) -minute chromospheric oscillation; “Coronal Bullseyes” appearing as radially decaying periodicities over sunspots and sporadic foot-point regions; and “Penumbral Periodic Voids” appearing as broad rings around sunspots in 1600 and 1700 Å in which spectra contain no statistically significant periodic component.

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1. Introduction

Studies of power spectra are common in solar physics and are used to provide insight into physical processes from the photosphere out to the solar wind. Many of these studies rely on Magnetohydrodynamic (MHD) or Reduced MHD (RMHD) simulations of small regions of the corona. Central to these investigations is the study of turbulence or, more specifically in the solar case, MHD turbulence, which is frequently proposed as a mechanism for transferring energy from the denser and cooler photospheric regions to the diffuse and super-heated outer corona. While MHD turbulence differs from fluid turbulence, a Kolmogorov-like turbulent cascade is frequently cited as a plausible means for coronal heating (van Ballegooijen (1986); Heyvaerts and Priest (1992); Einaudi et al. (1996)). Furthermore, turbulence - and specifically turbulence driven by wave reflection within the corona - has been proposed to play a key role in fast solar wind acceleration and can be related to the turbulent power spectra observed in the solar wind further out in the heliosphere (Verdini, Velli, and Buchlin, 2009). On small spatial scales, several authors have studied spectra from coronal loop simulations (e.g., Dmitruk and Gómez (1997); Dmitruk, Gómez, and Matthaeus (2003); Rappazzo, Velli, and Einaudi (2010); Taroyan, Erdélyi, and Bradshaw (2011)), generally finding power spectra in these regions to be well described by large power-law indices (corresponding to slopes of -2 to -3). A high-level overview of the characterization of coronal turbulence is given by Zhou, Matthaeus, and Dmitruk (2004), who review the energy spectra of MHD turbulence in several special cases and provide references to theoretical derivations of spectra properties in different turbulence regimes under many complex scenarios.

Observation-driven spectral analysis includes the works of McIntosh and Smilie (2004); McIntosh, de Pontieu, and Tomczyk (2008); Reznikova et al. (2012); Reznikova and Shibasaki (2012); Jess et al. (2012), who leveraged high-resolution space-based observations to focus on spatially small regions (e.g., sunspots and loops), typically examining only limited frequency ranges of the full power spectrum (e.g., 3-5 minute oscillations). Ground-based observations have been used to study localized chromospheric regions (e.g., Reardon et al. (2008); Tziotziou et al. (2007) and many more), but the emphasis is primarily on isolation of specific frequencies, rather than a broad analysis of the entire available power spectrum. Observations from the Transition Region and Coronal Explorer (TRACE; Handy et al. (1999)) were put to similar use by Muglach (2003), who performed a detailed study of the oscillatory nature of sunspot regions, and by McIntosh and Smilie (2004) who applied wavelet-based techniques to study oscillations in limited regions of interest in the photosphere. Furthermore, the energy of MHD waves propagating upward from the chromosphere to the corona has long been believed to be a contributor to coronal heating (Alfven and Lindblad (1947), recently summarized by Arregui (2015) and references therein), and thus studies of coronal oscillations and waves, and their damping properties, is of key importance to the understanding of the very broad topic of coronal heating (Parnell and Moortel, 2012).

With the advent of high-temporal resolution observations from SDO, a number of new studies relating to power spectra (or Fourier Transform and wavelets)
have arisen. For example, Reznikova et al. (2012); Reznikova and Shibasaki (2012) considered the periodic spectral properties of a sunspot across multiple wavelengths, have exploited the high temporal and spatial resolution of the SDO/AIA instrumentation and focused on spatially small areas and isolated features. Threlfall, Moortel, and Conlon (2017) combined SDO/AIA disk observations with white light observations from the Solar Terrestrial Relations Observatory (STEREO) to trace periodic signatures from the solar disk out into the heliosphere. Meanwhile the power-law behavior of solar power spectra have been increasingly investigated in a number of studies such as Inglis, Ireland, and Dominique (2015); Auchère et al. (2016). A more general approach by Ireland, McAteer, and Inglis (2015) used a power-law + tail + localized Gaussian model to describe solar power spectra from NASA Solar Dynamics Observatory Atmospheric Imaging Assembly (SDO/AIA) images and noted that select solar features appear to have different characteristic power spectra. Despite an increased focus on power spectral behavior in the solar corona, there have been no published global studies beyond Ireland, McAteer, and Inglis (2015), who considered average spectral properties in large regions across broad frequencies and for two wavelength channels, to investigate the broad spectral properties of all solar coronal features across spatially large regions and multiple wavelength channels.

In summary, theoretical or simulation-based models of turbulence (MHD or Reduced MHD) in the corona, and the power spectra that result from these models, apply directly to many key unanswered questions in solar physics involving energy transfer, wave propagation, coronal heating, and solar wind turbulence. Such studies require both high temporal and spatial cadence measurements sufficient to enable high-precision spectral analysis of coronal observations. In recent years, most notably with the launch of the SDO, data of sufficient temporal and spatial resolution have become available, but techniques needed to derive the properties of power spectra over both large regions and at high spatial resolution have not been developed.

Our work begins by extending Ireland, McAteer, and Inglis (2015) by averaging spectra over much smaller regions (3x3 vs. ~50x50 pixels). In addition, instead of considering select sub-regions containing a given feature in the AIA images and then computing a best-fit model for the average power spectra of all pixels in the sub-regions, we compute a best-fit model for each pixel at the center of a 3x3 pixel sub-region in a 1600x1600 pixel (~1000x1000 arcsecond) AIA image and then study the relationship between the spatial distribution of the best-fit model parameters and features in the AIA image. We also provide an improvement to the model by replacing the Gaussian term with a more physically meaningful Lorentzian to better describe the damped oscillatory features observed in many coronal power spectra. The presented methodology can be used to (1) support simulation-driven studies with observation-based spectra at high spatial and temporal resolution, (2) provide observation-based studies with a framework that enables the exploration of spatially large regions at full spatial and temporal resolution and across multiple wavelengths, and (3) enable the parameterization of large regions of the solar disk based on the properties of a two- or three-component power spectral model.
In this work, we provide details on the methodology, apply it to a 12-hour time interval of images from four wavelength channels of the SDO/AIA instrument, and then highlight a number of key discoveries and observations found in this application.

2. Data and Methodology

2.1. Data Selection

Our analysis uses data recorded by the Atmospheric Imaging Assembly (AIA) (Lemen et al., 2011) instrument on the NASA Solar Dynamics Observatory (SDO) (Pesnell, Thompson, and Chamberlin, 2012) on June 26, 2013, from 00:00:00 to 11:59:59 UT. The AIA instrument observes at wavelengths of 94, 131, 171, 193, 211, 304, 335, 1600, and 1700 Å at 4096x4096 pixel resolution (corresponding to a spatial resolution of approximately 1.67 arcseconds per pixel) and with a nominal cadence of 12 seconds in each wavelength channel (24 seconds for 1600 and 1700 Å).

The selection of this time interval was motivated by a desire to study a morphologically diverse corona, on a spatially global scale, in a single analysis; the selected region contains three diverse solar features: an active region (AR-1777), a coronal hole, and a filament. Also a factor in the choice of time interval was that no major flares or eruptions occurred, as we are still investigating the impact of such events on our analyses. Figure 1 shows a 171 Å image during the selected time interval, with a white box indicating the specific sub-region of interest.

We present results obtained from AIA images in the 171, 193, 304, and 1700 Å wavelength channels. We omitted analysis of 131, 335, and 94 Å because their higher noise levels created problems with spectral curve fitting and we omit analysis of 211 Å because of the similarity of results with 193 Å. We also omit a full presentation of the 1600 Å results primarily because of the similarity with that of 1700 Å but also as 1700 Å has less transition region contamination than 1600 Å making it a better representation of the chromospheric continuum (Lemen et al., 2011). For each of the used wavelengths, we selected a 1600x1600 pixel sub-region centered on the solar disk, as indicated in Figure 1. To aid with interpretation of our results, we also obtained a single Helioseismic Magnetic Imager (HMI) Magnetogram and HMI Continuum image from the middle of our sequence (June 26, 2013 06:00 UT), but note that these were used for qualitative analyses only, and thus no calibrations were performed on these data.

2.2. Data Preparation

Data were obtained from the Virtual Solar Observatory (VSO) (Hill et al., 2009) using routines in the SunPy package (SunPy Community et al., 2015). All analyses were performed using Python along with the NumPy and SunPy packages, with visualizations created with the MatPlotLib package.

Our analyses focus on a sun-centered 1600x1600-pixel region. For each of the considered AIA wavelengths, the observed cadence was 12 or 24 seconds,
Figure 1. AIA 171 Å full-disk image indicating the region of analysis (white box) considered for AIA wavelength channels 171, 193, 304, and 1700 Å. This image was recorded on June 26, 2013 at 05:59:59 UT.

although sporadic data gaps of up to ~90 seconds were encountered. For each wavelength, we extracted the 1600x1600-pixel Sun-centered region for each time step, compiled them into a single data cube, and then applied SunPy’s differential_derotation function\(^1\) so that each image is presented as if from the perspective of an observer rotating at the same rate as the solar equator, with corrections applied to account for differential rotation of the solar atmosphere. All images were divided by their exposure time to create what we refer to as normalized intensity images.

Figure 2 shows the arithmetic mean of the normalized intensity images\(^2\) of all four wavelength channels under investigation, as well as the corresponding region in HMI magnetogram observations (Panel (b)). Figure 2(a) shows sample locations referenced in later Figures 3 and 4; these locations were selected as representative of four broad categorizations of power spectra and are located on specific coronal features: a filament (Point A), a coronal hole (Point B), a small bright loop foot-point (Point C), and a sunspot umbra (Point D). Figure 2(b) shows the HMI Magnetogram observation corresponding to this region of inter-

\(^1\) Available in the latest release of Sunpy, v0.8.5

\(^2\) All observations in a given sequence were corrected for exposure time, then summed into a single image and divided by the number of images in the sequence to produce the images shown in Fig 2(a) and (c)-(f).
Following the differential rotation correction, we extracted the 12-hour time series of pixel intensities for each pixel in the 1600x1600 region for each wavelength. The spectra of these extracted time series (or light-curves) are the focus of this investigation. We note that we did not calibrate the raw images using the IDL-based \texttt{aia_prep.pro} routine that is often used for partial calibration of AIA observations. The omission of this pre-processing step means that, at the highest spatial resolution, we cannot precisely co-align images obtained from different AIA wavelength channels. However, the analyses presented here do not require such co-alignment.

To be able to use a Fast Fourier Transform (FFT) routine, we linearly interpolated across missing time values onto a uniform time grid corresponding to each wavelength’s nominal cadence, i.e., a time series obtained at nominal 12-second cadence, but with sporadic 24- or 36-second gaps, was linearly interpolated onto a 12-second time grid. Figure 3 shows four time series extracted at the sample locations indicated in Fig 2(a) after being interpolated onto a uniform time grid. No preprocessing of the time series beyond linear interpolation was performed. We experimented with the use of various forms of apodization and found that our interpretation and results were unchanged. Similarly, we found that the use of the Lomb-Scargle algorithm for computing the power spectrum (instead of using linear interpolation to fill data gaps and using the standard FFT algorithm) gave spectra that were effectively indistinguishable.

There exist a number of different methods for investigating time series in the frequency domain, with wavelet-based methods particularly common. To assess the compatibility between the often-used Morlet wavelet transformation and the FFT used here, we computed spectra from both of these methods, looking at their output over a broad range of spectra covering each spectral type discussed in our analysis. In general, the spectra returned by each method had largely the same shape (including no aliasing effects) and essentially identical periodicity locations (described in Section 2.3) for spectra in which a statistically significant Lorentzian fit was identified. Therefore, we are confident that our full-scale analysis would yield comparable overall results if replicated using wavelet-based methods of spectra computation. However, given that the transient behavior of interest is due to sinusoidal waves over many periods (as opposed to periodic spikes with broadband spectral content), the Fourier approach seems to be a natural choice.

2.3. Spectra Calculation

For reliable model fitting, we found it necessary to first perform a set of averaging steps to reduce the noise in the spectra. In the first averaging step, each 12-hour time series for a pixel is split into six non-overlapping two-hour segments and the arithmetic average of the six power spectra associated with these segments is computed. This averaging did not significantly affect the shape of the spectra but greatly reduced the noise. In the second averaging step, the arithmetic average of the previously computed spectra in 3x3 pixel-boxes around each pixel...
Figure 2. Average of normalized intensity images after deroration for each of the studied AIA channels from June 26, 2013 from 00:00:00 to 11:59:59 on a 1600x1600 pixel region centered on Sun-center for the 06 UT observation. Panel (a) indicates the locations associated with the sample time series and spectra presented in Figure 3 and 4. Panel (b) shows the corresponding HMI Magnetogram (06:00 UT observations) for this region of interest, and Panels (c)-(f) show the arithmetic average for each wavelength channels. The X- and Y-axes have labels for pixel value relative to Sun-center. The unit DN/s on the colorbar is described in the text.
Figure 3. Time series for the sample points A-D indicated in Figure 2(a). The titles in each panel include our characterizations of each point that are defined in Section 5.

is computed, with the result saved as the final spectra for the center pixel in the 3x3 box. To avoid edge effects from the 3x3 averaging procedure, a 1-pixel border was eliminated from the final data product, resulting in 1598x1598 spectra.

Without these averaging steps for the spectra, many model fits “failed” in the sense that they visually did not capture the gross features of the spectra, two visually similar spectra had very different fits, with one fit having a significantly larger data/model error, or the optimization routine would not converge at all. Details on these issues are given in Appendix A. Spectra computed using the two averaging steps resulted in few failed model fits for nearly all pixel locations.

The average spectra for the time series shown in Figure 3 are shown in Figure 4 as solid black lines. The other curves in Figure 4 are discussed in the following section.

2.4. Spectra Fitting

The spectral models used in this work are based on those used by Ireland, McAteer, and Inglis (2015), and we will follow the same parameter and model naming convention. The “M1” model for the power spectra, \( P \), consists of a power
law with a ‘tail’ and contains three parameters: the amplitude coefficient \( A \), the power-law index \( n \), and the ‘tail’ coefficient \( C \):

\[
M1: \quad P_1(\nu) = A\nu^{-n} + C. \tag{1}
\]

This model is not a true power law, but has a flattening above a frequency that is approximately determined by what we define as the rollover frequency,

\[
\nu_r = (C/A)^{-1/n}, \tag{2}
\]

or equivalently, the rollover period,

\[
T_r = (C/A)^{1/n}. \tag{3}
\]

the value of which is related to the photon noise amplitude in the observations. For values of \( \nu \) below \( \nu_r \), model M1 approaches a true power-law.

The M1 model is ‘nested’ within model M2. Ireland, McAteer, and Inglis (2015) presents the M2 as the sum of M1 and an additional Gaussian component. Our early work followed this same convention, but was recently modified to replace the Gaussian with a Lorentzian function, with the latter being more physically meaningful in the context of damped oscillations. Thus our M2 model takes the form:

\[
M2: \quad P_2(\nu) = A\nu^{-n} + \frac{\alpha}{\delta^2 \left( 1 + (\ln(\nu) - \beta)^2 \right)} + C. \tag{4}
\]

The additional parameters correspond to the Lorentzian component amplitude \( \alpha \), location \( \beta \), and width \( \delta \).

In practice, we found that in general the use of a Gaussian versus a Lorentzian does not produce significant differences in fit quality, with both functions able to describe the broad noise-dominated curves such as that observed in Fig 4(d). The Lorentzian provides a significantly improved fit over that of the Gaussian only in regions immediately surrounding sunspots. Given that certain periodic spectral features can be interpreted as the result of damped oscillations, with the full width half maximum (FWHM) of the curve serving as a proxy for amount of wave damping, we elected to use the Lorentzian for all analyses presented here for consistency. (Note, however, that although damped oscillations will produce a Lorentzian spectra, a spectra with a significant ‘M2’ component does not necessarily imply that it is explained by damped oscillations.) The Lorentzian equation used here is a modification of a standard Lorentzian in which we have added a necessary logarithmic term in order to capture the frequency-dependent width of the high frequency oscillations we observe in certain spectra. In this model, the width parameter \( \delta \) must be used with the location parameter \( \beta \) to find the FWHM in seconds:

\[
FWHM = 1/(e^{\beta+\delta} - e^{\beta-\delta}) \tag{5}
\]
and a large FWHM value corresponds to a small spread in the $P_2(\nu)$ spectra (small damping).

Many difficulties were encountered in attempting to produce a reliable algorithm to fit the spectra. We explored several fitting options, and the results presented here are based on the options that gave few failed fits and for which the successful spectral fits matched the data in a visually reasonable way and with a high data/model correlation. (To visualize the fits, a tool was developed that allowed us to select a pixel on a visual image and observe the corresponding spectral fit.) The average data/model correlation coefficient was 0.93 or greater for all of the wavelengths except for 1700 Å, which had an average correlation coefficient of 0.86.

We note here and detail in Appendix A that the values of the parameters computed in this work depend slightly on how many spectra were averaged for a given pixel, how many spectra from neighboring pixels were averaged, assumptions about the noise, and the optimization method used. Thus, different approaches to computing best-fit models may produce different best-fit parameters for the models, although we found that the Lorentzian component parameters of the M2 model were insensitive to the choice of averaging methods. Because the primary objective of this work is to identify spatial and relative-value differences in the best-fit model parameters and have few or no ‘failed’ fits, identification of a more accurate value of the M1 model parameters is less of a concern (and arguably not possible given the features of the time series described above and the assumptions that would be required for such an analysis).

Our model fitting procedure performs fits to both the M1 and M2 models and first compares the chi-squared values. If the chi-squared value of M1 is less than M2, the M2 fit is labeled as ‘failed’. The M2 model is expected to always produce chi-square values that are less than or equal to that of M1 because M2 is identical to M1 if the $\alpha$ parameter in M2 is set equal to zero. However, due to termination of the fitting procedure when changes in the error functions drop below our specified threshold, some spectra produce better fits to M1 than M2, and thus for those spectra we record only the three M1 model parameters. A successful fit of the M2 model does not necessarily imply that the included Lorentzian feature is meaningful in a statistical sense, and thus a second stage to our process is to use a hypothesis test to determine if M2, which has more parameters than M1, is better than M1. In Appendix A we detail the model fitting steps, and in Appendix B we detail the Lorentzian significance calculation.

Figure 4 shows the computed power spectra and resulting model fits of the sample time series shown in Figure 3. The four panels show the spectrum (black), the M1 model (blue) and the M2 model (purple), as well as the best-fit parameter values. The dashed vertical lines indicate the frequency corresponding to periods of 3- and 5-minutes, and $r$ is the correlation coefficient between the best-fit model (M1 or M2) and the averaged spectra. The parameter $p$ is the probability of rejecting the null hypothesis that M2 produces an equivalent (least-squares) fit to M1 when it is true. In this work $p < 0.005$ is the threshold at which we conclude that the M2 fit is statistically better than that of M1; the calculation of $p$ is described in Appendix B. Thus, in Figure 4 a Lorentzian component
Figure 4. Model fits and averaged spectra computed from the sample time series shown in Figure 3(a)-(d). The titles in each panel include characterizations of each point that are defined in Section 4.

(green dashed curve) is shown for all panels, but only that shown in Panel (d) is statistically significant and thus indicative of a periodic feature in the spectra.

In figures shown later in this manuscript, values for the Lorentzian location parameter in the M2 model, and the derived FWHM, are only shown at locations where \( p < 0.005 \). The titles of these figures include the percentage of the region in which the Lorentzian location values have been omitted (masked).

The spectral fitting procedure applied to each of the 1598x1598 pixels is computationally expensive, initially accounting for the majority of the approximately 30 hours required for processing each wavelength. Given the complexity of this process we used the \texttt{MPI4Py} package to implement a simple multi-threaded scheme in which the fitting calculations were distributed evenly among 16 virtual processing cores (8 hyper-threaded Intel i7 4.1Ghz/4.3Ghz processor cores) on a Linux-based desktop workstation computer. After parallelization, the total processing time was \( \sim 4 \) hours for each wavelength, 80\% of which was required for the spectral fits, roughly 10\% to load data from the FITS-format image files and derotate, and 10\% to compute and average the spectra. Speed-ups in processing time increased approximately linearly with number of processing cores until near

\[ \text{time} \times \frac{\text{cores}}{16} \]
system resource limits, and early indications are that this processing pipeline would port well to large multi-core High Performance Computing systems.

3. Results

The fitted spectral models provided us with the six parameters shown in Equation 4 for each investigated wavelength. In this paper, we focus on the results for three key parameters:

i) the power-law index, $n$, representing the slope of the power law;
ii) the Lorentzian location, $\beta$, representing the frequency of the peak of the fitted Lorentzian component of model M2; and
iii) the Full-Width Half-Maximum (FWHM) of the fitted Lorentzian curve.

As noted previously, the FWHM is a value derived from model fits, representing the width of the Lorentzian (analogous to a damping coefficient) in the temporal domain, with units of minutes. Other parameters, such as the Lorentzian amplitude and the M1 amplitude coefficient, as well as various quality of fit metrics, are retained but not presented. The results from these parameters, which do have certain unique features, will be the focus of subsequent investigations.

In the following subsections, we present the results for the four different AIA wavelengths in Figures 5, 6, 7, and 8. Panel (a) of each figure shows the arithmetically averaged visual image at that wavelength followed by the best-fit power-law indices in Panel (b), the Lorentzian locations in Panel (c), and Lorentzian FWHM in Panel (d).

3.1. 193 Å

Figure 5 shows the results for the 193 Å channel. Here we point to our first key result - namely that the visualization of all derived spectral parameters relate clearly, directly, and uniquely to features visible in the observational data. This result applies equally to every wavelength under consideration.

In Figure 5(b), we observe a clear difference between the coronal hole and surrounding active areas. The former has spectra that are far flatter than surrounding loops regions as a consequence of increased instrument noise (low signal) in the coronal hole. Magnetic loop structures are observed throughout the region with high power law indices approaching 2.5. Likewise, immediately below the coronal hole, the active region AR-1777 is well defined with high power-law indices. These large indices are widespread throughout 193 Å (and 211 Å, not shown), but are limited almost exclusively to coronal loop structures, with a possible inference being that flow along these loops is enabling fast energy cascades. A histogram of the power-law indices in this region is bell-shaped, and the peak value (mode) is 1.77, implying that classical Kolmogorov-like turbulence is pervasive throughout the hot corona.

The Lorentzian location and width panels in Figure 5(c) and (d) show the frequency (time) locations and widths (FWHM) of statistically significant ($p$ <
Looking carefully at the sunspot in Panel (c) reveals a central ~ 3-minute periodicity with a surrounding ring of ~ 5-minutes. We define this structure as a “coronal bullseye” - an approximately circular region of concentric\(^3\) rings of specific unique oscillatory periods, decaying radially from the center. Coronal

\(^3\)The discrete nature of the concentric rings is a function of the binning used for the colorbar; in actuality the periodicity falloff is continuous.
bullseyes are features we have observed in many other datasets not only sur-
rounding sunspots but also at the foot-points of sporadic loop structures. We
discuss these features further in Section 5. The Coronal Bullseye feature is seen
evolving more clearly as we describe the observations in the following sections.

Interpretation of Panels (c) and (d) is not trivial. The sunspot core and certain
points surrounding the active region (AR 1777) exhibit clear short-period (∼3-4
minute) oscillations, and these oscillations correspond to narrow Lorentzians in
the spectra (in the temporal domain), with FWHM values approximately on the
same order as the temporal frequency i.e., heavily damped. Surrounding the AR
we observe a fan-like structure of periodicities near 11-minutes, that themselves
contain irregularly shaped structures of approximately 5-minute periodicities.
These oscillations correspond to much wider Lorentzians, with widths on the
order of 18 - 30 minutes (i.e. less damping). Scattered around the upper-left of
Panel (c) we see a number of sporadic ∼ 4 minute locations that do not appear to
correspond to any obvious magnetic structures in the visual observation (Panel
(a)). These sporadic oscillatory features uniformly have FWHM values around
6 - 10 minutes i.e. approximately twice the oscillation period. We note that
these oscillatory features are observed in the same locations of the corona in the
171 and 304 Å observations, but do not correspond to any apparent feature in
1700 Å.

More broadly scattered throughout Panel (c) are a number of ∼ 11 minute
oscillations, with those that relate to bright points in the visual observations
having central regions of ∼ 5 minutes periodicities. The Lorentzians in these
features generally have inner FWHM values on the order of 10 - 14 minutes and
outer FWHM closer to 20 - 30 minutes, but the high degree of scatter in these
features makes this observation somewhat less certain.

Faintly observable in Panel (c) are narrow oscillatory structures (∼ 11 minute
periods) that seemingly trace magnetic field lines. These structures, an example
of which can be seen around pixel location [-300,-100], have much narrower
Lorentzians, with widths around 6 - 10 minutes i.e. again on the order of the
oscillation period, like the sunspot core. This implies that the strong magnetic
fields play a key role in the damping of oscillations, though the physical nature
of oscillations in the sunspot versus the loops is likely quite different.

We note finally that if we relax our significance constraint to, say, $p < 0.01$,
then many of the features seen here gain increased definition. However, the
relaxation of our $p$-value leads to excess noise in later figures, and thus for
this publication, we have chosen to retain a consistent (but perhaps overly
conservative) value of $p < 0.005$.

3.2. 171 Å

Figure 6 shows the results for the 171 Å observations. These observations cor-
respond to the upper transition region in the solar corona, and accordingly,
there are notable changes in the observed spectral properties concurrent with
the changed visible features seen at 171 Å, including contributions from hot
coronal lines as well as the underlying chromosphere.

The map of power-law indices shown in Figure 6(b) is similar in appearance
and interpretation to that of the 193 Å observations. The peak power law indices
are almost exclusively in areas of concentrated magnetic field (i.e., loops and footpoints), reaching values of around 2.2, with the coronal hole continuing to show very low power law slope values. In general, the distribution of power-law indices is shifted towards lower values (distribution peak at 1.67) and is of a slightly narrower range than in 193 Å, but with a longer tail for high index values than observed at 193 Å.

Figure 6(c) and (d), however, show a marked difference to 193 Å, with the overall structure appearing to mirror that of the underlying chromosphere, and noting an increase to approximately 37.9% coverage of statistically significant Lorentzian components in this wavelength. This growth comes partially from an apparent expansion of the ~11 minute features observed in 193 Å, though we can no longer resolve the ~11 minute “loop-like” structures. Many of the sporadic, isolated shorter-period features seen in 193 Å are now seen more clearly with ~4-minute periodicities that can also be traced to corresponding locations in 304 Å (presented next), and the fan-like structure around the AR is also essentially an expanded version of the 193 Å structure.

The Lorentzian widths (FWHM) seen in this channel have essentially identical properties to those discussed for 193 Å, with narrow widths in the sunspot core.
and in the sporadic ~ 4 minute points, more of which are now apparent in this channel (likely the result of chromospheric “leakage” in this channel), and the broader ~ 18 – 30 minute widths elsewhere.

3.3. 304 Å

Figure 7 shows the results for the 304 Å observations. These observations represent much lower temperatures (approximately 50,000 Kelvin) and processes more like photospheric/chromospheric than hot corona.

Accordingly, in Figure 7(b) we see globally lower power-law indices throughout this wavelength channel than observed in the hotter wavelength channels, with peak values around 1.7 and the lowest values around 1.1, and a distribution that peaks at 1.44. The structure in this image more closely mirrors the magnetic network structures observed in chromospheric and magnetogram observations. As with previous wavelengths, the peak index values correspond to the brightest regions in the visual observations and relate primarily to active region structures and loops (i.e., concentrated magnetic fields) that we suggest aid a relatively efficient energy cascade. We note also a broken chain of high power law indices that
follow the filament across the upper part of this region. The coronal hole remains clearly defined, demonstrating that regions with higher levels of instrument noise in low signal areas typically present low power law values (a notable exception being solar filaments, that have high power law slopes but also low signal/high noise).

In Figures 7(c) and (d), the Lorentzian parameters now occupy 62% of the region, again appearing as a natural “growth” of similar features seen in other wavelengths, particularly 171 Å. The scattered ∼ 5-minute periodicities are now prevalent, and larger in area, though upon close inspection appear quite disordered in their apparent periodicity over small (pixel-level) scales. This may be a resolution limitation of our approach, but could also be indicative of regions that have only quasi-stable periodicities or periodicities that exist over relatively short timescales. It is no longer possible to discern any clear pattern regarding the FWHM of the respective Lorentzians, but broadly we see that the distribution of widths is now dominated by much narrower ∼ 6 – 10 minute FWHMs.

The coronal bullseye in Panel (c) has a remarkably well-defined structure, with a central 3-minute periodicity, surrounded by a ring of 5-minute periodicities, and corresponds to the very narrowest end of the Lorentzian width scale. The ∼ 5 – 6-minute periodicities near the active region are better defined, partly due to a growth in the surrounding ∼ 11-minute region. These features form an approximately 90-degree arc of ∼ 5 – 6-minute periodicities forming a chain-like structure from pixel location [-200,-600] to [0,-400] that corresponds directly to higher power-law indices seen in the same location in Figure 7(b). This may be due to a loop oscillation; Aschwanden and Schrijver (2011), for example, report 6.3-minute period oscillations in a coronal loop, but this was a decay event following an M2-class flare; no such eruptive event was observed in this sequence. Otherwise, the higher power law indices in Figure 7(b) do not visually correspond with any periodic value in Figure 7(c), and in fact, more typically correspond to masked locations in the Lorentzian parameterization, implying a different mechanism is at work close to the AR versus similar areas at distance from the AR.

3.4. 1700 Å

Figure 8 shows the results for the 1700 Å observations. These lower temperature (upper photosphere/chromosphere) results are markedly different from the previously discussed wavelengths. While not shown here for reasons of brevity, the results for 1600 Å observations are essentially identical to those shown below, except where noted in the text.

In Figure 8(b), we see the power-law indices to be smaller across the entire region with maximum values of ∼ 1.57 and a histogram distribution peak at 1.22. Reinforcing our previous observations, the largest index values are found along magnetic network structures, though in this channel in particular the power law

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As noted earlier, the Rollover Frequency, $\nu_r$, (not presented) is an excellent metric for determining the point at which photon noise dominates a given spectrum, and highlights extremely well the low-signal features such as coronal holes.
index parameterization produces a map remarkably reminiscent of the magnetic network.

The Lorentzian results shown in Figures 8(c) and (d), with only 0.2% masking, are consistent with (Leighton, Noyes, and Simon, [1962]) — namely that the photosphere is dominated by a near-uniform, global oscillation. Our model fits consistently show a global oscillation near 4 minutes, which, upon inspection of the histogram of Lorentzian location values in this image shows a very clear distribution peak centered at 4.19-minutes ($\sigma = 0.33$ minutes). Equivalent analysis of the 1600 Å observations for this region have a similar distribution, with peak at 4.07 minutes ($\sigma = 0.30$ minutes). These results are consistent with McIntosh and Smillie (2004), who reported a global wavelet power peak of 4 mHz (4.13 minutes) in 1700 Å observations from TRACE using a spectral (wavelet-based) technique.

As with the power law indices, both Lorentzian components in Panels (c) and (d) clearly mirror the magnetic network. However, we note that the Lorentzians in 1700 Å are (relatively) broader in regions of strong magnetic field (i.e. magnetic network). These broader Lorentzians also correspond to regions of 5-minute oscillations, with a possible interpretation being that the 5-minute oscillations originate from the photosphere (per Leighton, Noyes, and Simon [1962]), us-

**Figure 8.** Results for the AIA-1700 Å channel with the same format as Figure 5.
ing the magnetic network as the conduit. Global oscillations distant from the magnetic network are more controversial in origin, thought to be the result of a reflection from the overlying transition region, trapping waves within a so-called “chromospheric cavity” (Carlsson and Stein, 1999; Taroyan and Erdélyi, 2008). These oscillations, including the determination of a constant offset of peak dominant oscillations between 1600 Å and 1700 Å, are the focus of a paper currently in preparation by this manuscript’s authors (Battams, Gallagher, and Weigel, In Preparation).

Generally speaking, we see FWHM values of \(\sim 5 - 7\) minutes close to the more magnetically active areas in this region (e.g., AR-1777), and wider Lorentzians \(\sim 8 - 11\) minutes throughout the remainder of the region. An exception is the much wider \((\sim 12 - 15\) minute) FWHMs corresponding directly to the regions of \(\sim 5\) minute oscillations in the magnetic network, and also observed scattered throughout as isolated pixels.

Within the coronal bullseye, we do not observe the same smooth graduation of periodicities outward from the center as seen in 304 Å, 171 Å and 193 Å. Instead, inside the sunspot umbra, there is a \(\sim 3\)-minute periodicity that is sharply bordered by a very thin transition ring that separates the inner region from an outer region of \(\sim 5\)-minute periodicity. The 3- and 5-min features are expected, being well-documented and discussed in the literature (e.g., Yuan et al. (2014); Bogdan and Judge (2006); Moortel (2009)) and serve as validation that our technique is accurately describing oscillatory phenomena. Despite low signal inside the sunspot umbra, we are confident that the values presented here are both real and correct.

At the outer edge of the coronal bullseye, there is a circular region (white ring) surrounding the sunspot, corresponding approximately to the sunspot penumbra, in which no Lorentzian component of significance is found. This feature constitutes another key finding of this investigation - namely that of a feature we label “Penumbral Periodic Voids” (PPVs). We have observed such PPVs surrounding every sunspot we have investigated in 1700 Å and 1600 Å observations. The PPVs we observe are not due to low signal, as the signal amplitude in the PPV is comparable to other regions (and much higher than that within the sunspot), or due to poor fits, as these regions have high data/model correlations of \(\sim 0.95\). We discuss the PPV features further in Section 5.

The spectra in the transition ring between the 3-minute circle and 5-minute ring appear fundamentally different from that in the PPV in that they seem to be a result of a broad mix of several periodicities in the 3- to 5-minute range, whereas the PPVs are simply an absence of any statistically significant periodicity. The PPV and this transition ring may be related to the “regions of lower power” reported by Muglach (2003), though Howe et al. (2012) report a contrasting result obtained from SDO observations in which spectral power is observed to be enhanced in a region surrounding a sunspot. Our results hint that both could be correct, as we do indeed see very closely bordering weak and strong spectral signatures at certain frequencies. A detailed study of this, and

\(^5\)Currently more than two dozen other sunspots have been investigated, the results of which will be presented in a follow-up work.
Table 1. Average data/model correlation coefficients ($r$) and their standard deviation ($\sigma$) for each wavelength considered, and the mean values across all wavelengths.

| Wavelength Å | Mean r | $\sigma$ |
|-------------|--------|---------|
| 193         | 0.98   | 0.03    |
| 171         | 0.96   | 0.05    |
| 304         | 0.93   | 0.06    |
| 1700        | 0.86   | 0.08    |
| All channels| 0.93   | 0.06    |

comparison with these previous related studies, is beyond the scope of this initial results paper.

4. Discussion of Results

4.1. Model Fitting

In Table 1, we provide the mean data/model correlations for the power spectra models for each wavelength considered. For every pixel location, we calculated the average correlation coefficient $r$ between the best-fit model (M1 or M2) and the averaged power spectra. From this table, we see that the best model fits are for the 193 Å observations, with $r = 0.98$ and a standard deviation of 0.03, and the EUV corona (193, 171, and 304 Å) models have a consistently higher $r$ than the chromospheric (1700 Å) fits.

The mean $r$ of 0.86 reported in Table 1 for 1700 Å is somewhat misleading regarding the quality of fits in that wavelength channel, which are highly feature-dependent. In the region surrounding the sunspot, including the coronal bullseye region, and in essentially all regions corresponding to the underlying magnetic network, the model fits are excellent, with correlations in the range 0.95-0.97. The average correlation is pulled down by the relatively poor fits found in the centers of convective cell structures, the power spectra of which are not well described by the model M2 (either with a Gaussian or a Lorentzian), and also in the very center of sunspot umbrae where powerful Lorentzians dominate the spectra. We plan to investigate adding a third model to future iterations of our technique designed to better fit the power law component of the 1700 Å observations, which may be more accurately represented by a broken power-law.

As we have noted, a certain number of fitting attempts failed to produce a meaningful fit to the M2 model, and instead we reverted to the parameters from the simpler M1 model. In theory, M2 should be adequate for all spectra as it is equal to M1 when Lorentzian components are set equal to zero. However, in cases
where the spectra in question is essentially just a pure power law, the curve fitting algorithm still attempts to incorporate the Lorentzian model components, and thus results in a poorer fit. The percentage of M1 fits in each channel were as follows: 193: 21%; 171: 11%; 304: 3% and 1700: 0%. These values are supportive of a narrative of power-law processes being relatively more dominant in the upper hot corona versus the power-law + oscillations dominating the lower/cooler/denser corona (adopting an admittedly naive stratified coronal model). Finally we note that in none of these “rejected M2” spectra is a legitimate Lorentzian feature being erroneously omitted, and thus we currently have no plans to address the sporadic bad fits to M2.

4.2. Limitations of Approach

While the approach presented here holds promise for a variety of studies of solar atmospheric dynamics, turbulence, and wave propagation, there are limitations of note. Most of these limitations may be mitigated through improved analysis procedures, but some are simply inherent to the observations.

Power spectra extracted from a full 12-hour time sequence, or even from shorter sequences, are inherently noisy, leading to high uncertainties in model fit parameters. We reduced the noise by averaging spectra temporally in 2-hour time series sequences and spatially over 3x3-pixel regions, enabling far better fits to the observations. However, this means that our spectra are perhaps better considered as 12-hour summary spectra, representing the average spectral conditions of a pixel location over a 12-hour window. In validation tests, this averaging was found to have the greatest impact on the low end of the frequency spectrum and thus has the greatest influence on the power-law index value. A slightly better power-law fit may be obtained by using longer time series (because additional low-frequency points are used in the fit), but with the trade-off of increased noise and a lower success rate in model fits. The high-frequency end of the spectrum, and thus the Lorentzian (or Gaussian) parameters, are largely insensitive to the length of the time series used, with the latter in particular being more reliant on a high temporal resolution to fully capture that end of the spectrum. There is clearly a need for investigation of better noise-reduction methods that would enable the use of shorter time intervals to allow a better representation of the time evolution of spectral properties, but the obvious visual correspondence between the original data and model parameterizations support a conclusion that a 12-hour window is capable of accurately capturing and representing the spectral behavior of a given region.

In this work, we selected a time interval without large-scale dynamic events. It is not possible to avoid all dynamic activity in the solar corona, as most features on all scales are constantly in motion. However, by avoiding major impulsive (e.g., flares) or eruptive events (e.g., filament eruptions), we are confident our spectra do not include a bias from major events. However, our method is then also unlikely to capture short-duration events that may be of interest due to the use of a 12-hour window. Thus use of this technique requires consideration of the time-series length under investigation to ensure that dynamic events are included or excluded as desired.
On smaller scales, particularly in the hotter corona, we observe coronal loops in apparent motion. In some cases, these may be loops that are physically moving, but may also be representative of situations in which, for example, one loop is cooling while a nearby loop is heating, giving the appearance of physical motion of a single loop. There is no simple solution here - the corona is inherently highly dynamic and loop motion, whether apparent or real, is not trivial to correct without complex feature tracking and modeling. Furthermore, the spectral properties of the AIA filters are such that some channels include many different emission lines that provide an additional layer of complexity for analysis. We have intentionally omitted this consideration from the presentation of these early results, but note that future studies using this technique will certainly need to incorporate a thorough understanding of the different spectral components in each channel. Furthermore, care would need to be taken if this technique were used to follow the behavior of a single loop structure, for example, but this is a challenge faced by all such studies and is perhaps more of a data limitation than a methodology limitation.

An additional complication for our technique arises due to the possible superposition of features within the corona. To some extent our approach assumes the corona to be a flat plane, whereas, of course, it is a dynamic, optically thin 3-D structure. Thus, for example, large coronal loop structures can be seen arcing high above the lower corona. In such a situation, even assuming a static loop, any given pixel will contain dynamic intensity (and spectral) contributions from both the loop and the underlying corona. Furthermore, the derotation algorithms applied will be incapable of properly correcting an ‘optically deep’ field of view. However, as our results show (particularly in the hot corona), loop structures are clearly defined in all aspects of our parameterizations, and our approach is again validated by the obvious visual correspondence between the parameterizations and the underlying observations.

5. Spectra Categorization

Components of coronal power spectra can be broadly described as either “turbulent”, “periodic”, or “quiescent”, with corresponding spectral characteristics of a power-law, a Lorentzian peak, and a flat region (referred to as the power-law tail). Per the plot captions in Figures 3 and 4, we broadly categorize power spectra as (1.) Tail dominated without a Lorentzian (Panels (a) and (b) in Figures 3 and 4); (2.) Power-law dominated and a without Lorentzian peak (Panel (c) in Figures 3 and 4) (3.) Power-law dominated with Lorentzian (Panel (d) in Figures 3 and 4). These spectral features correspond directly to the visually observed features in the corona, many of which persist throughout the different heights of the corona. It is important to note that while the power-law and Lorentzian features are a consequence of physical processes, the power-law tail is essentially a consequence of reaching a noise floor (photon noise) in the observations.
5.1. Tail dominant regions without Lorentzian

A power-law with a tail component is required to suitably characterize the quieter regions of the corona that have a white noise (flat) spectra above a certain frequency. These regions are best characterized by the rollover period parameter in our models, which is the period below which the spectra ceases to be well-represented by a power-law and instead are better fit with a flat spectra. Thus, the interpretation should be that large rollover periods imply a smaller power-law frequency range and a larger white noise (photon noise) frequency range in the spectra.

In Panels (a) and (b) of Figures 3 and 4, we showed two time series and their corresponding model fits extracted from regions whose spectra can be broadly described as “tail dominant without Lorentzians”. Specifically here, these time series and their corresponding spectra were obtained from points identified in Figure 2(a) that were within (i) a filament and (ii) a coronal hole. Other filaments that we have studied have similar traits in that their power-law slope is larger than those observed in coronal holes, particularly at cooler temperatures, but they both have wide frequency ranges with a flat spectra. Our interpretation is that the larger power-law index in the filament is, in part, a consequence of the closed magnetic field nature of that structure, versus the open fields of the coronal hole, that better facilitates an energy cascade in those regions. However, this observation is dominated by the simple fact of filament structures having far better signal to noise ratios than coronal holes. Nonetheless, studies of the spectral turbulence (or lack thereof) in coronal holes may have application to studies of the turbulence in the fast solar wind that originates from these otherwise spectrally quiescent regions. These results may also have relevance to the understanding of the interplay between magnetic and kinetic energy in the corona; simulations such as (Rappazzo et al., 2008) have found large power-law indices in magnetically-dominated regions and flat spectra in regions dominated by kinetic energy.

Despite long tails being directly associated with higher levels of noise in the observations, we do still observe usable signal in these areas. Thus, despite the increased photon noise in, say, coronal holes, the structures and features revealed in the parameterization of their spectra warrant investigation, and thus it is important that spectral modeling can accurately capture and describe these properties. Though on this point we note that high levels of noise encroach upon the low-frequency end of the power spectrum, leaving us with fewer points on which to fit a power law. Thus, while we do believe the power law nature of this data to be ‘real’, the exact value of the slope may have more uncertainty than in spectra with shorter or non-existent tails.

5.2. Power-law dominant regions without Lorentzian component

Broadly speaking, most coronal regions can be described to some approximation by a simple power law, with power-law indices confined within the approximate range of 1.1 to 2.5 in the presented observations (but exceeding 3.0 in other data sets we have surveyed). A typical power-law dominant spectrum is shown in
Figure 4(c), corresponding to Point C in Panel (a) of Figure 2, which is a small and bright loop region. These highest power-law indices are almost exclusively observed in coronal loops at high temperatures (on the order of $10^6$ K). This finding is consistent with the spectral index found in simulations of coronal loops (e.g., (Rappazzo et al., 2007; Rappazzo et al., 2008; Müller and Grappin, 2005; Matsumoto, 2016)). The broad interpretation here is that strong concentrations of magnetic fields facilitate a rapid cascade of energy through the spectrum and result in high power-law indices. Regions with shallower slopes would presumably be experiencing processes that inhibit the cascade of energy.

More generally, all solar power spectra appear to contain at least some component indicative of turbulence. Intuitively, this is to be expected as was noted by Ireland, McAteer, and Inglis (2015): “[the power law fit is] consistent with the idea that the solar atmosphere is heated everywhere by small energy deposition events.” However, our results over large spatial regions show a broad range of power-law indices, all of which relate directly to specific visible features, and the ranges of which appear to be related to the characteristic temperature of the corona. In the characteristically cooler wavelengths (304 and 1700 Å), we see that the steepest power-law indices relate to the strongest magnetic features: the active regions and magnetic network. These power-law index results mirror those found in simulations (e.g., Kitiashvili et al. (2015)) at these characteristic temperatures in the solar atmosphere. Again, we assume the same interpretation as for the hot corona - namely that strong magnetic fields channel MHD waves and facilitate a rapid cascade of energy through the spectrum. At these cooler temperatures, this process is seemingly impeded, resulting in the slower cascade and hence shallower overall power-law indices. An alternate interpretation relates to our observation of 5-minute oscillations throughout the magnetic network, which imply these structures may be facilitating the passage of slow magnetoacoustic waves from the underlying photosphere (Bogdan, 2000; Roberts, 2006; Vecchio et al., 2006) and thus the power law slope here result from fundamentally different processes in ‘cool’ versus ‘hot’ corona.

5.3. Power-law dominated with Lorentzian

Periodic features are observed throughout the solar atmosphere. Generally, the Lorentzian component locations are found at the high-frequency end of the spectrum, per Figure 4(d), which corresponds to Point D in Figure 2 and is situated near the sunspot in AR-1777.

The first observation we note is a general one - namely, that at characteristically cooler/lower heights in the corona, significant Lorentzian components become more prevalent, reaching almost complete coverage in 1700 Å. That periodic waves do not propagate throughout the entire corona is expected, but this result may be valuable for understanding exactly where certain waves are being “lost” in the solar atmosphere. In 304 Å for example, we see many examples of 5-minute periodicities scattered throughout the region, generally corresponding to the bright points in the observations, most likely the underlying magnetic network. Only a very small number of these are observed in 193 Å, implying that these waves are seemingly more effectively dissipated in the hotter corona.
The exception is around the sunspot, whose periodicity permeates all channels we investigated, and is extremely well-represented by the Lorentzian (damped oscillation) model. This is a result that closely mirrors the findings of Reznikova et al. (2012), who noted that “... the strong magnetic field of a sunspot works as a waveguide for the acoustic waves propagating from the photosphere level and eventually reaching a 1 MK corona.” At the photosphere and in 304 Å, we see almost a perfect series of concentric periodicities (as noted by Yuan et al. (2014), for example) around the sunspot; a feature we labeled a coronal bullseye, with the 3-minute central peak pervasive through to the 193 Å observations.

Our presentation of this structure may be related to observations reported in Reznikova et al. (2012) and Reznikova and Shibasaki (2012), in which contours of specific frequency ranges (2-3mHz, 3-4mHz and 5-6mHz) are shown for two different sunspots observed by SDO. Our approach differs in that instead of isolating specific frequencies or periods, we have instead included and visualized all frequencies, enabling the production of a full 2-D map of the periodicities surrounding sunspots (and around certain loop footpoint, as we have observed in datasets not presented here). In the 171 Å and 304 Å observations, the coronal bullseyes are particularly well-structured and defined, with radially decaying periodicities from a central peak of 3-minutes that rapidly, but smoothly, decays to approximately 11-minutes. This smooth decay is in contrast to the 1700 Å observations, in which no such decay is observed; instead the central 3-minute region is entirely isolated from an outer 5-minute region by a very thin, disorganized region of chaotic oscillations. A similar finding was reported by Tziotziou et al. (2007), who noted a rapid jump in oscillation period at the umbral-penumbra boundaries in Doppler observations. Our results further this by noting that this “jump” region sometimes contains a steep gradient of periodicities, but often (and particularly in 1600 Å) shows a complete lack of any statistically significant periodicities.

All Lorentzian features presented here have a corresponding derived FWHM, reported in the temporal domain (in units of minutes). As discussed in the previous sections, the relationship between Lorentzian location and FWHM is complex and both feature and wavelength-dependent. In the hot corona, magnetic structures (sunspot, loops) have the smallest FWHM that are similar to their periodicity. In the chromosphere (1700 Å), however, the magnetic networks have a larger FWHM that are two to three time that of their periodicity. The complexity of these relationships is such that a dedicated study is warranted here in which features are perhaps organized by type, physical mechanism, and wavelength, and the relationship between their periodicity and width studied in detail to gain an understanding of the damping mechanism(s) involved, if any. It is important to note that while we have presented the FWHM parameter as a potential proxy for damping of oscillatory processes, it is important to note that all Lorentzian-like spectral features observed in the corona are not necessarily a result of damped processes. Such features could also arise from multiple superimposed periodicities, for example. Indeed, we state that the Gaussian model proposed by Ireland, McAteer, and Inglis (2015) generally produces fits equally as good as a Lorentzian for all features, with the exception primarily of sunspot cores, for which our Lorentzian model is superior. Therefore we are confident...
that the FWHM is representative of damped processes in those regions at the very least, but feel it is an insightful metric throughout the corona, regardless of the driving mechanisms.

5.4. Periodic Penumbral Voids and Umbral-Penumbral Transitions

In Figure 8(c) and (d) we observed the feature we refer to as a Penumbral Periodic Void, or PPV - an annular region surrounding a sunspot in which no statistically significant periodicities are observed. As noted elsewhere, we have observed PPVs surrounding every sunspot in 1600/1700 Å data that we have investigated (currently more than two dozen). These features are obviously a consequence of some process or processes that impede or prevent the establishment of stable oscillatory behavior. This is likely related to the local magnetic field structure surrounding the sunspot, or perhaps indicative of an impairment of wave coherence around the sunspot (Zhao and Kosovichev, 2006).

Figure 9. Panel (a) shows the zoomed view of the active region and PPV shown in Fig 8(c) and (d), with spatial axes in units of pixels relative to solar disk center. Panel (b) shows the visual average intensity image for this 1700 Å observation and panels (c) and (d) show the corresponding solar region as seen in the Helioseismic Magnetic Imager (HMI) Magnetogram and HMI Continuum observations, respectively. Overlaid on panels (b,c,d) is a red outline that corresponds to the borders of the white areas (the PPV) seen in Panel (a) and the borders of the inner umbra-penumbra transition ring.

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In Figure 9 we provide a brief examination of both the PPV and an additional feature - an inner umbra-penumbra transition ring. These features are highlighted by a red outline (actually the significance mask we use to omit statistically insignificant results) overlaid upon the 1700 Å average intensity image (Fig 9(b)), and the corresponding Helioseismic Magnetic Imager (HMI) magnetogram (Fig 9(c)) and continuum (Fig 9(d)) observations.

The PPV (white ring in Fig 9(a)) is a broad feature both here and in the same 1600 Å observations (not shown), and bounds the entire sunspot. In comparison with animations of the corresponding magnetogram observations, and as is somewhat evident from Fig 9(c), we note the PPV appears to correspond extremely well with the location of Moving Magnetic Features (Vrabec, 1971; Harvey and Harvey, 1973; Wilson, 1973), the presence of which may be expected to impede coherent periodicities, either directly or as a consequence of the known chaotic or absent magnetic fields in regions close to magnetic fields (Ryutova et al., 1998).

We note also that the PPV observed in 1700 Å is not observed in the overlying corona (304 Å or above), with instead that region of the corona showing strong periodic features (coronal bullseye). Thus it seems the oscillations we observe in, say, 304 Å, are perhaps not driven from immediately below, but instead propagate through magnetic fields that come up from the sunspot and are draped over the PPV. Related to this is the observation that the PPV is essentially identical in both the 1600 Å and 1700 Å observations (the former not presented here), and thus given that both these channels are strongly continuum-dominated, the source of the PPV is itself likely rooted in the continuum, as opposed to having an origin in the weaker spectral lines within the relevant filters.

The second feature we draw attention to in Fig 9(a) is a so-called inner umbra-penumbra transition ring - a very narrow ring of chaotic periodicities that act as a border between the 3-minute umbral and 5-minute penumbral regions (all entirely inside the PPV). The transition ring shown here fully encircles the sunspot umbra, with a mixture of very steep gradients of periodicities, or regions absent of any periodicity, observed along much of its circumference. These features are common to both the 1700 Å and 1600 Å observations, with minimal differences observed between these two channels for any given date/time range.

It can not be conclusively determined from our observations whether the absence of statistically significant periodicities in this region arise from a lack of such signal (as is the case with PPVs), or is a result of a breadth of interfering signals or colliding waves within our 12-hour window. As shown in Fig 9(d), the inner umbral-penumbral transition ring encompasses the sunspot core as observed in HMI Continuum observations. This feature may therefore relate to the region at which inward and outward flows diverge (Sheeley et al., 2017); again, such a region would not intuitively be expected to maintain a coherent periodicity. However, as noted above, multiple observed periodicities in such a spatially small region may be complicating the signal we observe here. Nonetheless, the chaotic spectra seen in this narrow region is fundamentally spectrally different to any other region observed throughout all investigated AIA channels thus far.

Further analysis of these two features will require detailed study and models of the underlying magnetic fields, and perhaps considerations of moving magnetic
features, running penumbral waves and Doppler observations. Thus it is outside
the scope of this initial survey of results.

6. Summary

We have presented a new methodology, based upon the spectral models of
Ireland, McAteer, and Inglis (2015), that enables the pixel-level spectral pa-
rameterization of solar EUV observations. This powerful technique enables us
to reduce EUV intensity time series down to spectral model components that
can be used to both separate out and explore the different underlying physical
processes (i.e. power law versus oscillatory) occurring in any given pixel-level
location. We presented only results from two of the six model parameters - the
power-law index and the Lorentzian peak location - with a third parameter rep-
resenting the full-width half-maximum (FWHM) of the Lorentzian derived from
the model. We showed the spatial distribution of these parameter values map
directly to visible features in the EUV images and outline, for example, coronal
loops, bright points, coronal holes, sunspots, and the photospheric magnetic
network. We also demonstrated the complex feature-dependent relationships
between the location and width of observed Lorentzian features. The presented
method could be extended to facilitate the understanding of the transfer of en-
ergy throughout the corona via a number of different studies. For example, with
comprehensive calibration, the evolution of the power spectra for an individual
identified structure (e.g., a coronal loop) could be investigated as a function
of AIA wavelength, and compared to the spectra produced from the moderate
breadth of numerical simulations of coronal loops. Using our methodology, we
identify features in the locations of observed periodicity that we refer to as
“coronal bullseyes” (circular periodic structures found over sunspots but also
occasionally over coronal bright points), “Penumbral Periodic Voids” (PPVs;
circular rings surrounding sunspots, devoid of any inherent periodicity), and
“inner umbra-penumbra transition rings” (very thin rings of chaotic periodicity
acting as the boundary between 3- and 5-minute oscillations in sunspot cores).
Sunspots are observed here to have strong and radially decaying periodicities
with a bullseye-like structure with a 3-minute central periodicity observed in
all wavelengths, from the UV of the upper photosphere to the EUV of the
corona. Well-defined PPV rings were observed in photospheric observations, and
appear to correspond to the sunspot penumbra and may be a consequence of
Moving Magnetic Features in magnetogram observations (Harvey and Harvey,
1973). We also identify a spectrally unique region of chaotic periodicities at the
umbra-penumbra boundary, appearing as a narrow ring, which may be related
to diverging flows around the sunspot core (Sheeley et al., 2017).

Our methodology identified a global 4.05/4.19 minute oscillation in the AIA
1600/1700 Å observations. Other analysis methods, such as the wavelet analysis
used by McIntosh and Smillie (2004) returned results to within 0.07 minutes of
that detected by our analysis. More broadly, the 4-minute oscillation is a well-
known observation, though a literature search did not yield any specific studies
dedicated to exploring and characterizing the slightly different oscillations observed between 1600 Å and 1700 Å. These periodicities are explored further in a paper currently in preparation by this paper’s authors (Battams, Gallagher, and Weigel, In Preparation).

Regions of strong closed magnetic fields (e.g., coronal loops) were shown to have spectra with large power-law indices, while coronal holes and filaments have a wide range of frequencies with a flat spectra, but with steep initial power laws found in filaments, likely a result of their magnetic structure. Sporadic 5-minute oscillations are seen in 304 Å that readily pervade to 171 Å and, to a lesser extent, 193 Å.

Finally, we have shown that the FWHM of fitted Lorentzians - an analog for the damping coefficients - has a complex relations related to both the nature of the structures in which we observe them (e.g., coronal loops, sunspot, magnetic network), as well as the wavelength channel in which we observe them, with all showing ratios between 1 and 5 (i.e., Lorentzian widths are, at most, five times that of their period of oscillation). Such results warrant detailed investigation, and could reveal valuable insight into the different physical processes driving, modulating and damping oscillations throughout the corona.

Our approach could also be used for detailed studies of the propagation of waves throughout the solar corona, with the ability to track signals at the pixel level over spatially large regions. There is also opportunity to study transverse wave propagation around sunspots, for example, which in 1700 Å manifests as the “Penumbral Periodic Void” features in which the spectrum becomes essentially a pure power law throughout a ring surrounding the sunspot. Circular regions of both enhanced (Howe et al., 2012) and diminished (Muglach, 2003) spectral power have been noted in published literature. However, those observations are perhaps limited by the methodology used to uncover those phenomena, in which a narrow frequency range of the spectrum is considered. We expect that the presented method can be used to resolve discrepancies arising from previous studies by providing a spatial context and a complete spectral characterization over an entire region. Studies such as those by Reznikova et al. (2012), Reznikova and Shibasaki (2012), Tziotziou et al. (2007) appear to have seen facets of both PPVs and coronal bullseyes, but our methodology should now enable a full 2-D spatial investigation of periodicities in the corona, thus tying together such existing studies.

Acknowledgments KB was supported by the NRL Edison Memorial Program and the Office of Naval Research. The authors wish to thank Jack Ireland for his many inputs during discussion and assistance with model fitting validation. We are also grateful for the insights of an anonymous reviewer in a much earlier version of this paper that led to significant improvements in this study.

Appendix

A. Spectral Fitting

In this appendix, we give details on some of the considerations and issues involved with fitting a model to spectra computed from time series generated by
extracting intensity values from a single pixel over a 12-hour time interval. The nominal image cadence is either 12- or 24-seconds with few missing images (at most $\sim 3\%$). The time series were placed on a uniform 12- or 24-second time grid and the gaps removed using linear interpolation prior to computing the spectra.

To estimate the spectral model parameters, many methods were considered in order to address the following issues:

i) **Non-stationarity** - Over a 12-hour time period, the spectra at a given location may change from, for example, power-law + tail to power-law dominated. To address this, we can use shorter time segments to compute the spectra with the drawback of a possibly less accurate power-law index because the spectra will have fewer points at low frequencies.

ii) **Noise** - The spectra for a given 12-hour time series typically has a large noise amplitude, and as a result, ‘failed’ fits often resulted. A ‘failed’ fit is one in which the curve fitting routine produces a spectrum that visually does not match the spectra in a sensible manner or does not fit at all. We considered two approaches to reducing the noise: (1) computing the average of spectra derived from segments of the full time series and (2) computing the average spectra in a 3x3 pixel box, which has the drawback that neighboring pixels may not have the same spectral type.

iii) **Computation time** - Spectra with a large amount of noise take much longer to fit. As an example, when fits for 1600x1600 spectra are computed using no smoothing, the time was projected to be greater than $\sim 100$ hours compared to $\sim 4$ hours for the averaging method that was used.

Based on these issues and considerations, the method used for computing model parameters in this work is given as follows.

i) For each pixel, average the spectra from six 2-hour non-overlapping time segments from the full 12-hour interval;

ii) Average 9 spectra in a 3x3 box to compute the final spectra for a pixel at the center of the box;

iii) Compute parameter estimates using the Dog-Box method from the *SciPy optimize.curve_fit* version 0.18.1 package for Python 3.6.4 with parameter bounds given in Table 2 and uncertainties corresponding to the standard deviation of the nine spectra values used in the averaging described in (ii). For the 1700 Å channel, we used an uncertainty at frequency $f_i$ proportional to $\log_{10}(f_{i+1}/f_i)$ with the uncertainty for the highest frequency equal to that of the next-highest. This ad-hoc approach was taken for 1700 Å because it led to fewer failed fits and better fits from a visual perspective; and

iv) Use the best-fit parameters from the Dog-Box optimization as initial guesses for the TRF optimization method from *SciPy’s optimize.curve_fit* optimization package with the same parameter and uncertainties used for the Dog-Box optimization step.

The first two steps were needed to reduce the noise in the spectra and decrease the amount of time needed for each optimization. Because we wanted to keep our spatial features as sharp as possible, we used only a 3x3 spatial averaging...
Table 2. Parameter bounds used in model fitting.

| Parameter Constraints | Lower Bound | Upper Bound |
|-----------------------|-------------|-------------|
| $A$ | $0$ | $2 \cdot 10^{-3}$ |
| $n$ | $0.3$ | $6.0$ |
| $C$ | $-0.01$ | $0.01$ |
| $\alpha$ | $10^{-5}$ | $0.2$ |
| $\beta$ (mHz/min) | $1.5/11.1$ | $10/1.66$ |
| $\delta$ (mHz) | $0.05$ | $0.8$ |

window and then obtained additional smoothing from segmentation of the 12-hour interval. This combination seemed to be the least amount of averaging that was required to obtain few failed fits and for the computation to complete in a reasonable amount of time. Time segments of 2 hours in length were used because we found their power-law indices were similar to those obtained from using the full 12-hour segment, and when segments of 1 hour were used, the power-law indices began to show substantial differences.

The parameter ranges in Table 2 used for optimization were based on those used in Ireland, McAteer, and Inglis (2015) and were refined to those presented through a process of trial and error. The lower bound for $C$ was chosen so that its middle value was near the center of the histogram peak in resulting distributions. Our value of $n = 0.3$ is lower than that of Ireland, McAteer, and Inglis (2015) because our region of interest included a coronal hole, which we observe to frequently have such low power law indices.

The fourth step was introduced because although the Dog-Box method produced in general the best fits of the optimization methods in SciPy’s optimize.curve_fit optimization package, in some cases we found unphysical spikes in the histogram of the 1598 parameters for a given wavelength at values that were at the centers of the parameter bounds given in Table 2. This was found to be due to the fact that the Dog-Box optimization method uses the centers of the parameter bounds as the initial guesses, resulting in early termination of the minimization algorithm if a local minimum of the function happened to be found there. This issue was corrected by the use of a two-stage/step curve fit routine that used the Dog-Box method to compute initial parameter estimates that were then used as the initial estimates for a TRF optimization.

B. Significance Calculation

Model M1 has a total of $p_1 = 3$ adjustable parameters and Model M2 has $p_2 = 6$. As a result, M2 is expected to provide a better fit to the spectra on average. The $F$ test is used to determine when this is meaningful. The $F$-statistic associated with this test, which applies when M1 is nested in M2, is
\[ F = \left( \frac{RSS_1 - RSS_2}{p_2 - p_1} \right) \left( \frac{RSS_2}{n - p_2} \right) \]  \hspace{1cm} (6)
Rappazzo, A.F., Velli, M., Einaudi, G., Dahlburg, R.B.: 2007, Shear photospheric forcing and the origin of turbulence in coronal loops. The Astrophysical Journal 722(1), 65.

Rappazzo, A.F., Velli, M., Einaudi, G., Dahlburg, R.B.: 2007, Coronal heating, weak MHD turbulence, and scaling laws. The Astrophysical Journal 657(1), L47.

Rappazzo, A.F., Velli, M., Einaudi, G., Dahlburg, R.B.: 2008, Nonlinear Dynamics of the Parker Scenario for Coronal Heating. Astrophys. J. 677, 1348. DOI [ADS](10.1086/525129)

Rappazzo, A.F., Velli, M., Einaudi, G., Dahlburg, R.B.: 2008, Shear photospheric forcing and the origin of turbulence in coronal loops. The Astrophysical Journal 722(1), 65.

Ryutova, M., Shine, R., Title, A., Sakai, J.I.: 1998, A Possible Mechanism for the Origin of Emerging Flux in the Sunspot Moat. Astrophys. J. 492, 402. DOI [ADS](10.1086/305328)

Shakura, N.I., Thesis, J.R., Thomassie, J.C., Warren, H.P.: 2017, Tracking the Magnetic Flux in and around Sunspots. Astrophys. J. 836, 144. DOI [ADS](10.3847/1538-4357/aa82b0)

SunPy Community, Mumford, S.J., Christe, S., Perez-Suarez, D., Ireland, J., Shih, A.Y., Inglis, A., Liedtke, S., Hewett, R.J., Mayer, F., Hughitt, K., Freij, N., Meszaros, T., Bennett, S.M., Malocha, M., Evans, J., Agrawal, A., Leonard, A.J., Robitaille, T.P., Mampaey, B., Campos-Rozo, J.I., Kirk, M.S.: 2015, SunPy-Python for solar physics. Computational Science and Discovery 8(1), 014009. DOI [ADS](10.1098/rsctc.2015.1709)

Taroyan, Y., Erdélyi, R.: 2008, Global Acoustic Resonance in a Stratified Solar Atmosphere. Solar Phys. 251, 523. DOI [ADS](10.1007/s11207-007-9232-8)

Taroyan, Y., Erdélyi, R., Bradshaw, S.J.: 2011, Observational Signatures of Impulsively Heated Coronal Loops: Power-Law Distribution of Energies. Solar Phys. 269, 295. DOI [ADS](10.1007/s11207-010-9732-2)

Threlfall, J., Moortel, I.D., Conlon, T.: 2017, Above the noise: The search for periodicities in the inner heliosphere. Solar Physics 292(11). DOI [ADS](10.1007/s11207-017-1191-3)

Tziotziou, K., Tsiropoula, G., Mein, N., Mein, P.: 2007, Dual-line spectral and phase analysis of sunspot oscillations. Astron. Astrophys. 463, 1153. DOI [ADS](10.1051/0004-6361:20066415)

van Ballegooijen, A.A.: 1986, The Cooling of a Sunspot. III: Recent Observations. Astrophys. J. 311, 1001. DOI [ADS](10.1086/165044)

Velev, M., Einaudi, G., Dahlburg, R.B.: 2008, Nonlinear Dynamics of the Parker Scenario for Coronal Heating. Astrophys. J. 677, 1348. DOI [ADS](10.1086/525129)

Velev, M., Einaudi, G., Dahlburg, R.B.: 2008, Shear photospheric forcing and the origin of turbulence in coronal loops. The Astrophysical Journal 722(1), 65.

Verdini, A., Velli, M., Buchlin, E.: 2009, Turbulence in the sub-alfvenic solar wind driven by reflection of low-frequency alfen waves. The Astrophysical Journal 700(1), L29. DOI [ADS](10.1088/0004-637x/700/1/l29)

Vrabc, B.: 1971, Magnetic Fields Spectroheliograms from the San Fernando Observatory. In: Howard, R. (ed.) Solar Magnetic Fields, IAU Symposium 43, 329. ADS

Wilson, F.R.: 1973, The Cooling of a Sunspot. III: Recent Observations. Solar Phys. 32, 435. DOI [ADS](10.1007/BF00150285)

Yuan, D., Sych, R., Reznikova, V.E., Nakariakov, V.M.: 2014, Multi-height observations of magnetoacoustic cut-off frequency in a sunspot atmosphere. Astron. Astrophys. 561, A19. DOI [ADS](10.1051/0004-6361/201322267)

Zhao, J., Kosovichev, A.G.: 2006, Surface magnetism effects in time-distance helioseismology. The Astrophysical Journal 643(2), 1317. DOI [ADS](10.1086/503248)

Zhao, J., Mattaeus, W., Dmitruk, P.: 2004, Colloquium: Magnetohydrodynamic turbulence and time scales in astrophysical and space plasmas. Reviews of Modern Physics 76(4), 1015. DOI [ADS](10.1103/revmodphys.76.1015)