



**AUTOMATED SUNSPOT CLASSIFICATION AND
TRACKING USING SDO/HMI IMAGERY**

THESIS

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AFIT-ENP-MS-16-M-083

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Captain, USAF

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Abstract

HMI Intensitygram and Magnetogram images from the National Aeronautics and Space Administration (NASA) Solar Dynamics Observatory (SDO) provide the best spatial and time resolution imagery available for sunspot analysis. The quality and quantity of this data provides an opportunity to analyze the sunspot detection and classification ability of an automated MATLAB code created by Spahr (2014). SDO/HMI data is analyzed for the period 1 July 2013 through 31 July 2015. Automated McIntosh classifications from the Spahr code are compared against sunspot reports from the National Oceanic and Atmospheric Administration's (NOAA) Space Weather Prediction Center (SWPC) using a three-tiered comparison metric. Statistical confidence is demonstrated for algorithm performance and consistency when compared against the SWPC data set, suggesting future applications of the Spahr algorithm will perform similarly. A sunspot tracking algorithm is added to the Spahr code to allow for feature tracking across multiple solar images. Reliable feature tracking is demonstrated for time periods out to four days between consecutive images. Feature tracking is a foundational step toward automated analysis of sunspot dynamic morphology and connections to solar events such as solar flares. Finally, an empirical Mount Wilson Magnetic Classification algorithm is generated and added to the research code. Early testing of the magnetic classification output against SWPC data sets is discussed and demonstrates a viable prospective application, achieving a direct match of 79.78% with SWPC magnetic classifications.

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MacLane A. Townsend

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AUTOMATED SUNSPOT CLASSIFICATION AND TRACKING USING SDO/HMI IMAGERY

I. Introduction

1.1 USAF Space Weather Operations

The 2nd Weather Squadron (2WS) of the 557th Weather Wing leads all characterization and forecasting of space weather phenomenon for the United States Air Force (USAF). Official observations of the Sun take place at five sites geographically spread out around the globe to ensure continuous “eyes-on” the Sun (AFWAMAN15-1). These solar observing sites measure full spectrum radiation emitted from the Sun and alert forecasting centers to significant changes to solar output. Three of the observatories make up the Air Force Solar Observing Optical Network (SOON) which measures radiation emitted from the Sun in the visible spectrum.

A highly active Sun can send large quantities of energetic particles and photons hurling toward the Earth by means of solar flares and coronal mass ejections (CMEs). These solar ejecta cause an assortment of negative impacts to USAF operations to include radio communication interruption, magnified GPS error, and even increased satellite drag.

In order to measure the current structure and cycle of the Sun, sunspots are documented at least once daily by 2WS solar analysts. Current procedures dictate that observers manually draw sunspots on a sheet of paper using a projected visible image of the photosphere and then classify each sunspot group according to the McIntosh classification system. Sunspot observers produce these drawings during times of optimal solar visibility with as few obscurations, such as clouds, as possible (AFWAMAN 15-1). Once sunspot characterization is complete, observers coordinate with NOAA’s Space

Weather Prediction Center (SWPC) in Boulder, CO for official sunspot classification and record keeping.

1.2 Limitations

Two immediate limitations exist in current sunspot observing procedures. First, manually drawing sunspot features means that observations are limited by the solar analyst's ability to see sometimes very small features of the Sun's photosphere, and inconsistencies between analysts are expected even with standardized training. Second, sunspot observations are currently based on solar sensors situated on Earth's surface. This fact means that any given observing location is limited to approximately twelve hours of sunlight per day, and atmospheric weather conditions may limit the amount of solar radiation reaching the sensor. As a result of these restrictions, sunspot drawings from any given location are occasionally unavailable for a day or more. Automated sunspot detection and classification using satellite imagery mitigates both of these limitations by increasing the consistency in sunspot classifications and allowing for a longer observing period with fewer interruptions.

1.3 Previous Research

The McIntosh classification system, developed in 1966 as a supplement to the Zurich classification method, provides the modern sunspot characterization rules and allows for sixty possible unique sunspot characterizations (McIntosh, 1990). Automation of this classification system has seen an increasing trend over the last two decades with different studies utilizing digital photosphere intensity imagery from various ground-based solar observatories (Benkhalil et al., 2004; Qahwaji and Colak, 2005), the Solar and Heliospheric Observatory (SOHO) satellite (Howard, 2015; Watson and Fletcher, 2010; Watson, 2012), and more recently the Solar Dynamics Observatory (SDO) satellite (Spahr, 2014). Each study follows a similar method of image preprocessing in order to

isolate and detect solar features, with image resolution and background contrast being the primary limiting factors to accurate sunspot detection (Aschwanden, 2010). These studies generally achieve successful detection of solar features, but matching automated classification to existing sunspot observations has proven more difficult. Studies have been completed to incorporate machine-learning techniques in order to better mimic human classification (Qahwaji and Colak, 2006). Such use of neural networks may be required to replace existing human classification methods, but ultimately these systems carry with them the same bias seen in manual classification.

Early solar observers recognized a correlation between solar flares and the presence of sunspots on the solar surface (McIntosh, 1990). In depth analysis comparing sunspot characterization to solar flare occurrences has been used to deduce the individual contributions of each McIntosh classification parameter to an overall likelihood of solar flare occurrence (Bornmann and Shaw, 1994). Sunspots are the visible indicator of magnetic flux through the solar surface, and changes in this flux are thought to be our best indicator of explosive solar activity (Murray, 2012). As such, sunspot activity is important to USAF knowledge of space weather conditions, and therefore a system built to better analyze the dynamic nature of sunspot evolution might bring greater insight into predicting and mitigating solar impacts.

1.4 Research Objectives

Recent employment of modern solar observing satellites, namely NASA's Solar Dynamics Observatory (SDO), makes available large volumes of high resolution imagery. It is generally accepted that utilization of this vast amount of data is only possible through automated processes that take careful consideration of image processing techniques applicable for solar features (Aschwanden, 2010). Spahr (2014) developed a MATLAB code designed specifically to detect and classify sunspot groups automatically using SDO/HMI Intensitygram and Magnetogram images. Analyzed data spanned July

2012 through June 2013 and was compared against official USAF (Holloman) and SWPC sunspot observations. Howard (2015) extended this research and code to SOHO/MDI imagery in order to analyze a wider time period from 1996 to 2011. Both studies demonstrated a reliable automated detection and classification scheme.

The objective of this thesis is to extend the research of Spahr and Howard by analyzing SDO data from July 2013 through July 2015, taking time to examine differences in code performance between analysis periods. Additionally, a sunspot tracking algorithm will be added to the code in order to examine the temporal evolution of detected sunspots. Finally, an empirical Mount Wilson magnetic classification algorithm will be added to the existing code to further analyze sunspot groups. With these additions in place, the output of this research code will provide the same level of sunspot characterization employed by SWPC manual solar observers. These objectives lay the groundwork for future research into solar flare prediction, allowing for automated analysis of high volumes of solar sunspot data and the corresponding magnetic structure of solar active regions.

II. Background

This chapter provides information on appropriate solar physics concepts and data sources needed for this research topic. The solar cycle and sunspots are discussed to provide foundational knowledge necessary for sunspot characterization. The McIntosh classification system and Mount Wilson magnetic classification system are illustrated for reference. A description of the SDO data to be used is provided with further details about the automated classification approach.

2.1 Solar Cycle

Consistent observation of the Sun by early astronomers allowed for the discovery that our Sun exhibited a cyclical pattern of activity with an average period of 11 years (Foukal, 2013). A reliable way to measure this cycle is through observation of sunspots on the photosphere, though many other solar parameters vary greatly over this period including x-ray and radio wave emissions. George E. Hale first recognized the connection between the solar magnetic field and sunspots and concluded that the Sun in fact undergoes a 22-year cycle that spans two magnetic polar reversals, each lasting on average 11 years (Babcock, 1961). The Babcock model later expanded on the nature of the solar magnetic field suggesting that the field is created through dynamo processes in the convective zone of the Sun with magnetic field lines running parallel to lines of constant longitude below the solar surface, exiting near the poles, resulting in a poloidal magnetic field (Babcock, 1961). As a solar cycle progresses, differential rotation of solar plasma, with faster rotation occurring near the equator, results in magnetic field lines gradually winding up beneath the photosphere due to ‘frozen-in’ field conditions (Foukal, 2013). A more concentrated magnetic field results and field lines begin to push radially through the solar surface in the form of magnetic flux tubes due to magnetic buoyancy (Babcock, 1961). Sunspots are the visible result of these flux tubes.

Each new solar cycle starts with a near north-south orientation of sub-surface magnetic field at solar minimum. The gradual winding of the field lines means that, over time, the regions of maximum magnetic concentration first appear at intermediate latitudes ($\sim 30^\circ$ north or south) and gradually intensify and drift toward the solar equator reaching 8° north or south approximately 8 years later (Babcock, 1961). This process is described by Spörer's law. Solar maximum sees the highest number of sunspots located at, on average, the lowest latitudes. The culmination of this cycle is the neutralization and reversal of the dipole magnetic field due to severing and reconnection of field lines above solar active regions with the field lines of the main dipole field (Babcock, 1961).

Each 11-year solar cycle is given a numeric identifier to distinguish it from prior cycles. We are currently in Solar Cycle 24 which began in January 2008. There is some debate as to when the peak in activity of Solar Cycle 24 occurred, but early 2014 seems most likely. As a consequence, the automated sunspot analysis using SDO imagery started by Spahr (2014) and continued in this study will span the lead-up to peak intensity and the ensuing drawdown of sunspot activity in Cycle 24.

2.2 Sunspots

Sunspots develop when concentrated magnetic field lines begin to emerge from the photosphere, directed outward toward the solar corona. The plasma within these field lines remains isolated from the surrounding solar surface due to a condition called a 'frozen-in' magnetic field (Foukal, 2013). The orientation and strength of the local magnetic field hampers solar convection below the flux tube, resulting in fewer plasma particles within this region. Pressure and temperature within the flux tube both decrease while magnetic pressure keeps the flux tube from collapsing inward (Foukal, 2013). This temperature drop results in less spectral intensity emitted from within the sunspot compared to the surrounding solar surface consistent with Planck's law,

$$B(\lambda, T) = \frac{2\pi hc^2}{\lambda^5} \frac{1}{e^{\left(\frac{hc}{\lambda kT}\right)} - 1} \quad (1)$$

where λ is wavelength of the light, h is Planck's constant, c is the speed of light, k is the Boltzmann constant, and T is temperature of the emitting surface in Kelvin. The lower temperature means the curve of the Planck function above peaks at longer wavelengths, no longer in the visible spectrum and resulting in the darker appearance.

The dark black region of a sunspot is called the umbra, which is characteristic of a near vertical orientation of the local magnetic field (Foukal, 2013). A penumbra may develop on more mature sunspots on the outer edge of the umbra. The penumbra appears slightly brighter than the umbra, but still darker than the surrounding solar surface. This is due to the Evershed effect, where magnetic field lines leaving the sunspot have a larger horizontal component, allowing for increased plasma flow and increased convection below the penumbra (Foukal, 2013). The result is a higher temperature and brighter appearance than in the umbra.

Sunspots usually develop as part of a larger group. Within the group, leading and trailing spots correspond with opposite magnetic polarity (Foukal, 2013). Additionally, the leading (or preceding) spot will have the same polarity as other leading spots in the same hemisphere, while leading spots in the opposite hemisphere will have the opposite polarity according to the Hale-Nicholson polarity law (Hale and Nicholson, 1925), seen in Figure 1. These bipolar magnetic regions (BMR) first develop with leading and trailing (or following) spots close together, both propagating east to west, or left to right from the viewpoint of Earth. Gradually, the distance between leading and trailing spots will increase (Babcock, 1961).

As mentioned above, the plasma density and temperature within a magnetic flux tube are lower than the surrounding solar surface. This changes the optical properties of the sunspot. The Wilson effect describes how the opacity within a sunspot decreases compared to that of the average photosphere, resulting in an apparent topographical

depression within the sunspot (Foukal, 2013). Umbrae lie at the base of the depression and penumbrae line the slopes of the depression. As a result, sunspots entering or leaving the limb of the solar disk will have their umbra disappear from view due to the viewing angle of the observer (Watson et al., 2009). Automated sunspot classification schemes must be aware of the apparent change in sunspot shape during progression near the solar limbs.

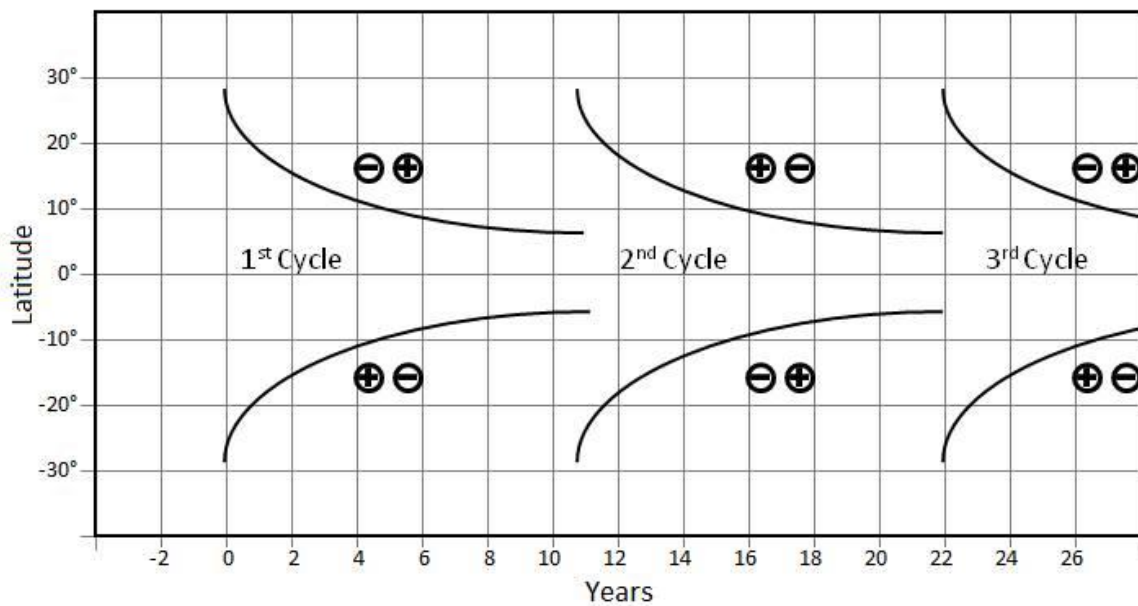


Figure 1. Spörer's Law and Hale-Nicholson Polarity Law. Curved solid lines represent expected average sunspot location north or south of the solar equator over the course of a solar cycle. Circles depict magnetic polarity of leading and trailing sunspots and the magnetic reversal between solar cycles.

2.3 McIntosh Classification System

Modern sunspot classification follows the three-component McIntosh scheme developed in 1966, supplementing the previous Zurich classification system (McIntosh, 1990). This system characterizes individual sunspots or sunspot groups based on size, orientation, area, density of spots within the group, and fullness (McIntosh, 1990).

Classification is presented as a three-letter identifier, or 'Zpc', code with each letter corresponding to a respective classification tier. Figure 2 illustrates each letter descriptor.

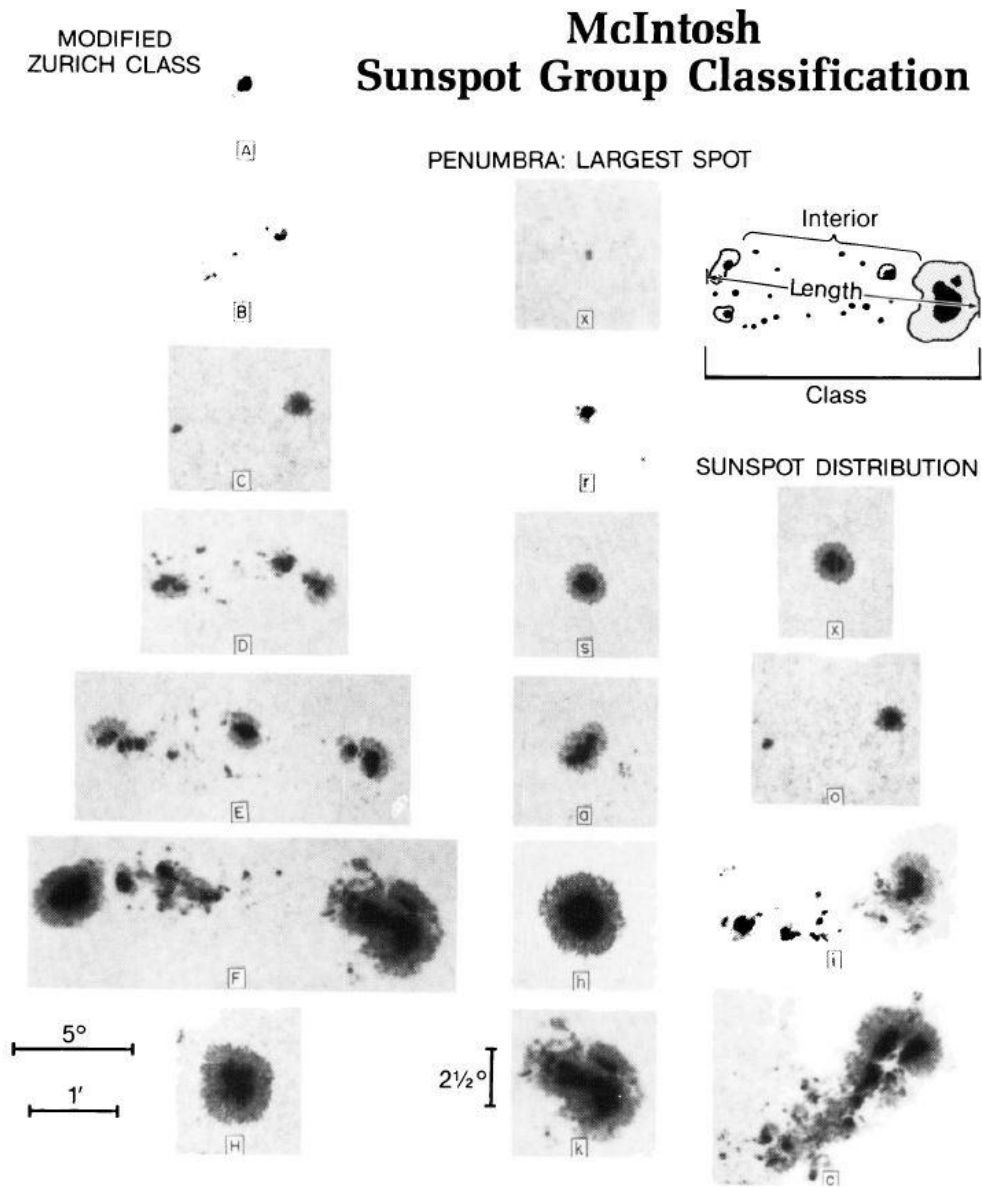


Figure 2. McIntosh Sunspot Group Classification (McIntosh, 1990)

2.3.1 Modified Zurich Class – ‘Z’

The first classification tier is the modified Zurich classification. This code describes the size and/or length of a single sunspot or sunspot group and whether penumbra is visible and, if so, how it is distributed (McIntosh, 1990). Note that length is measured using heliographic degrees as depicted in the left column of Figure 2. Table 1 below lists possible ‘Z’ letter identifiers. Additional references to Zurich classification later on in this document are referring to the modified Zurich class of the overall McIntosh classification system.

Table 1. Modified Zurich, ‘Z’, Classification Letter Identifiers (McIntosh, 1990)

A	Unipolar group (single spot) with no penumbra, representing either the formative or final stage of evolution in a spot group.
B	Bipolar group without penumbra on any spots.
C	Bipolar group with penumbra on one end of the group, in most cases surrounding the largest, or leader, umbrae.
D	Bipolar group with penumbra on spots at both ends of the group and length $\leq 10^\circ$.
E	Bipolar group with penumbra on spots at both ends of the group and length defined as: $10^\circ < \text{length} \leq 15^\circ$.
F	Bipolar group with penumbra on spots at both ends of the group and length $> 15^\circ$.
H	Unipolar group with penumbra. The principal spot is usually the leader spot remaining from a pre-existing bipolar group.

2.3.2 Penumbra of the Largest Spot – ‘p’

The penumbra descriptor of the McIntosh classification system expresses the type, size, and symmetry of the penumbra of the largest spot in the group (McIntosh,

1990). This tier is illustrated by column two of Figure 2, and Table 2 describes possible ‘p’ identifiers.

Table 2. Penumbra, ‘p’, Classification Letter Identifiers (McIntosh, 1990)

x	No penumbra (corresponds to ‘Z’ class of A or B).
r	Rudimentary penumbra partially surrounds the largest spot. This penumbra is incomplete, granular rather than filamentary, brighter than mature penumbra, and extends as little as 3 arc sec (2200 km) from the spot umbra.
s	Small, symmetric penumbra. Largest spot has mature, dark, filamentary penumbra of circular or elliptical shape. The north-south diameter across the penumbra is $\leq 2.5^\circ$.
a	Small, asymmetric penumbra. Penumbra of the largest spot is irregular and multiple umbrae within the penumbra may exist. North-south diameter of penumbra $\leq 2.5^\circ$.
h	Large, symmetric penumbra. Same structure as type ‘s’, but north-south diameter of penumbra $> 2.5^\circ$. Area must be ≥ 250 millionths of a solar hemisphere (MoSH).
k	Large, asymmetric penumbra. Same structure as type ‘a’, but north-south diameter of penumbra $> 2.5^\circ$ and area ≥ 250 MoSH.

2.3.3 Sunspot Distribution – ‘c’

The third tier of the McIntosh classification system describes the relative spot density between the leading and trailing spots of a group, often referred to generally as the compactness of the sunspot group. This tier is illustrated by the third column in Figure 2. The distribution of spots within the group serves as an indicator of the

irregularity of the magnetic field in that region of the photosphere (McIntosh, 1990).

Descriptions for the ‘c’ identifiers are given in Table 3.

Table 3. Compactness, ‘c’, Classification Letter Identifiers (McIntosh, 1990)

x	Undefined for magnetic unipolar groups (‘Z’ class A and H).
o	Open group. Few, if any, spots between leader and follower spots. Interior spots of very small size.
i	Intermediate group. Numerous spots lie between the leading and following spots. No interior spots possess penumbra.
c	Compact group. Area between the leading and following spots is heavily populated with at least one interior spot possessing mature penumbra. The extreme case of compact distribution has the entire group enveloped in one continuous penumbral area.

2.4 Mount Wilson Magnetic Classification System

In addition to the McIntosh classification system, several solar observing entities, including SWPC and USAF solar observatories, determine the Mount Wilson magnetic class of each sunspot group (AFWAMAN15-1). The McIntosh classification system deals more with the visible appearance of the sunspot group, while the Mount Wilson classification system characterizes the north and/or south magnetic polarity of the sunspot group. Magnetogram images, as discussed below, are the primary tool for classifying the magnetic structure of sunspot groups. Common practice by USAF solar observatories is to classify a sunspot group with one of seven possible Mount Wilson Classifications, seen in Table 4 (AFWAMAN15-1; AFAN15-124).

Table 4. Mount Wilson Magnetic Classification Codes

Alpha	Unipolar (single magnetic pole) sunspot groups
Beta	Bipolar sunspot groups with a simple and distinct division between areas of opposite polarity
Beta-Gamma	Bipolar sunspot groups with no easily discernible dividing line separating areas of opposite polarity
Gamma	Complex sunspot groups with areas of opposite polarity completely intermixed, preventing classification as a bipolar group
*Delta	Denotes sunspot groups consisting of opposite polarity umbrae within the same penumbra
*Note that the classification code 'Delta' is not a standalone magnetic classification. It is simply a descriptor that can be affixed to the end of the 'Beta', 'Beta-Gamma', and 'Gamma' classification codes, allowing for a total of seven unique magnetic codes.	

2.5 Solar Dynamics Observatory

The SDO satellite, launched in February 2010, is the first mission in NASA's Living With a Star (LWS) program. The objective of the mission is to image the solar atmosphere over a broad spectrum of wavelengths with high spatial resolution on short time scales in order to advance knowledge about the Sun-Earth relationship (Pesnell et al., 2012). The SDO satellite was positioned into a circular geosynchronous orbit with an inclination of 28°. This orbit results in near continuous observation of the Sun with the exception of a 2-3 week period twice per year in which view of the Sun is briefly blocked each day by the Earth (Pesnell et al., 2012). SDO carries with it three scientific instruments: the Atmospheric Imaging Assembly (AIA), the EUV Variability Experiment (EVE), and the Helioseismic and Magnetic Imager (HMI). Each instrument monitors and images the Sun at specific wavelengths in order to study diverse solar features. The two

solar images used for this research are created by the HMI instrument and are described further below. The HMI instrument is designed to measure the Doppler shift, intensity, and vector magnetic field at the solar photosphere using the 6173 Å Fe I absorption line with a spatial resolution of one arcsecond, or 725 km (Schou et al., 2012).

The SDO/HMI imager is a charge-coupled device (CCD). CCDs measure the intensity of the source light, or number of photons, by use of the photoelectric effect. Detected photons are ‘binned’ together into pixels in order to represent the detected object. A slight problem arises from this practice since a near continuous span of light intensity coming from the object is represented by pixels of definite size with discrete boundaries. As a result, the binning causes each pixel to represent the average intensity value of photons falling in the pixel’s dimensions, creating a small quantification error. Note that this error is inherent in all digital images, and the higher the resolution of the image, the smaller the error due to the smaller relative size of each pixel.

2.5.1 HMI Intensitygram

The first image used in this research is the HMI Intensitygram (HMII). Intensitygrams generally plot the white light intensity of the Sun, and therefore are very useful in detecting solar features at visible wavelengths such as sunspots. Many ground based observatories and other solar observing satellites provide these images. The HMII differs from most other continuum intensity images in that the intensity of visible light leaving the photosphere is inferred from only the 6173 Å spectral line (Scherrer, 2012) and therefore does not measure the full continuum of white light. Spahr (2014) recognized the potential error in using sunspot classifications derived from the HMII images and making comparisons with sunspot classifications made from white light sources. He addresses this issue in his thesis and concludes that any difference between SDO HMII products and other white light intensitygrams is negligible. A colorized

intensitygram, abbreviated HMIIC, is made available by SDO and is utilized for this research. An example HMIIC image is shown in Figure 3.

2.5.2 HMI Magnetogram

The other image used in the research code is the HMI Magnetogram, also referred to as a line-of-sight magnetogram in order to distinguish from vector magnetograms. Line-of-sight magnetograms can only measure the component of the solar magnetic field parallel to the observer's line of sight. Again, magnetograms are produced by many solar observing sources, and are used to track variations in the solar magnetic field at the photosphere. Typically, magnetograms are gray scale images with white shaded regions implying outward directed magnetic field lines and black representing inward directed magnetic field lines. Shades of gray denote no net line-of-sight magnetic field. HMI Magnetogram images use the Zeeman splitting of the 6173 Å spectral line to measure the Stokes parameters and determine the magnetic polarity of solar active regions (Pesnell et al., 2012). The grayscale SDO Magnetograms utilized in this research are abbreviated HMIB. An example HMIB image is shown in Figure 3.

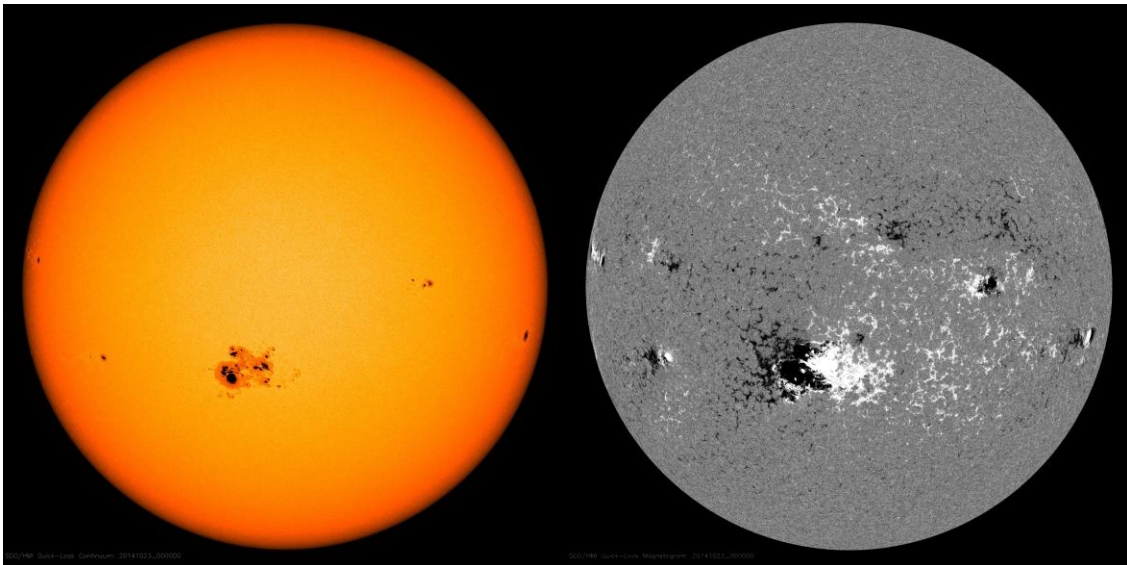


Figure 3. Example HMIIC Image (left) and HMIB Image (right). All solar images are used courtesy of NASA/SDO and the AIA, EVE, and HMI science teams.

2.6 Remote Sensing Considerations

All of what we know concerning the Sun is deduced from distant measurements, a method referred to as remote sensing. Observers positioned millions of miles away from the Sun provide our observations, but various optical features must be considered to ensure that we are correctly interpreting the information received.

2.6.1 Limb Darkening

The solar surface, also called the photosphere, is not a surface as we might expect with solid objects. The Sun is a hot dense gas throughout, and the layers of its atmosphere are only observable at certain wavelengths of light. The photosphere consists of a layer approximately 500 km thick that is defined more accurately using an optical depth framework (Foukal, 2013). The intensity of light passing through hot solar gases will be reduced as the gases absorb the light as described by the Lambert-Beer law,

$$I = I_0 e^{-\tau} \quad (2)$$

where τ is the optical depth, I_0 is the intensity of light emitted at the solar surface, and I is the intensity of light reaching the observer. When viewing solar light in visible wavelengths, or more accurately at the hydrogen α wavelength of 6562 Å, the photosphere is the region of the solar atmosphere where $\tau = 1$ (Foukal, 2013). Due to the natural exponential in the Lambert-Beer law, this implies that only 37% of the source light from the photosphere is reaching our sensors. Optical depth depends on plasma density. Since density varies radially away from the solar core, optical depth will likewise vary radially. For reference, a larger value of optical depth would suggest we are looking deeper into the sun, but in return we would see less and less of the source light intensity.

A problem arises when we consider viewing angle. An observer looking directly at the center of the solar disk would see the photosphere at an optical depth of one

because the angle, ρ , between the line of sight of the observer and the normal direction to the photosphere is zero. As the observer begins to move their gaze toward the limb of the solar disk, ρ increases. As a result, the observer is looking into the sun at an oblique angle, and the added horizontal component of the viewing angle means that, in order to see the photosphere, the observer must look through more of the solar atmosphere. The layer where $\tau = 1$ is now above the photosphere and is cooler than that of the solar surface (Foukal, 2013). According to Planck's law described in Section 2.2 above, the limb of the Sun appears darker due to this drop in temperature. This is known as limb darkening. The MATLAB code used for this research described later corrects for this phenomenon in order to accurately detect sunspots near the limb of the Sun.

2.6.2. Solar Axis Tilt

Due to the offset between the rotational axis of the Earth and Sun from the ecliptic plane, careful calculations must be made to determine the position of a feature on the solar surface as seen by an observer. The P angle is defined as the angle between the solar north pole and the celestial north pole from the observer's perspective. The B angle is defined as the angle of tilt of the solar north pole away from or toward the observer (Seidelmann and Urban, 2013). Both angles are dependent on time of the year and are calculated for this research as part of the ephemeris calculation described in Section 3.2.1. For reference, the P angle is calculated and corrected on all SDO images prior to public release (Pesnell et al., 2012; Schou et al., 2012; Scherrer et al., 2012). As a result, the MATLAB code for this research assumes a P angle of zero. Any application of this research code to images from sources other than SDO will need to apply the non-zero, time varying P angle calculated in the ephemeris algorithm.

Figure 4 below is a visualization of the solar coordinate system, which will be discussed further in the next section. For reference, the B angle and P angle are represented by the angles subtended by 1 and 2 respectively. The B and P angles are the

forward/back and left/right components of the apparent angle between the rotational axis, defined through R , and the celestial north pole, defined through R' .

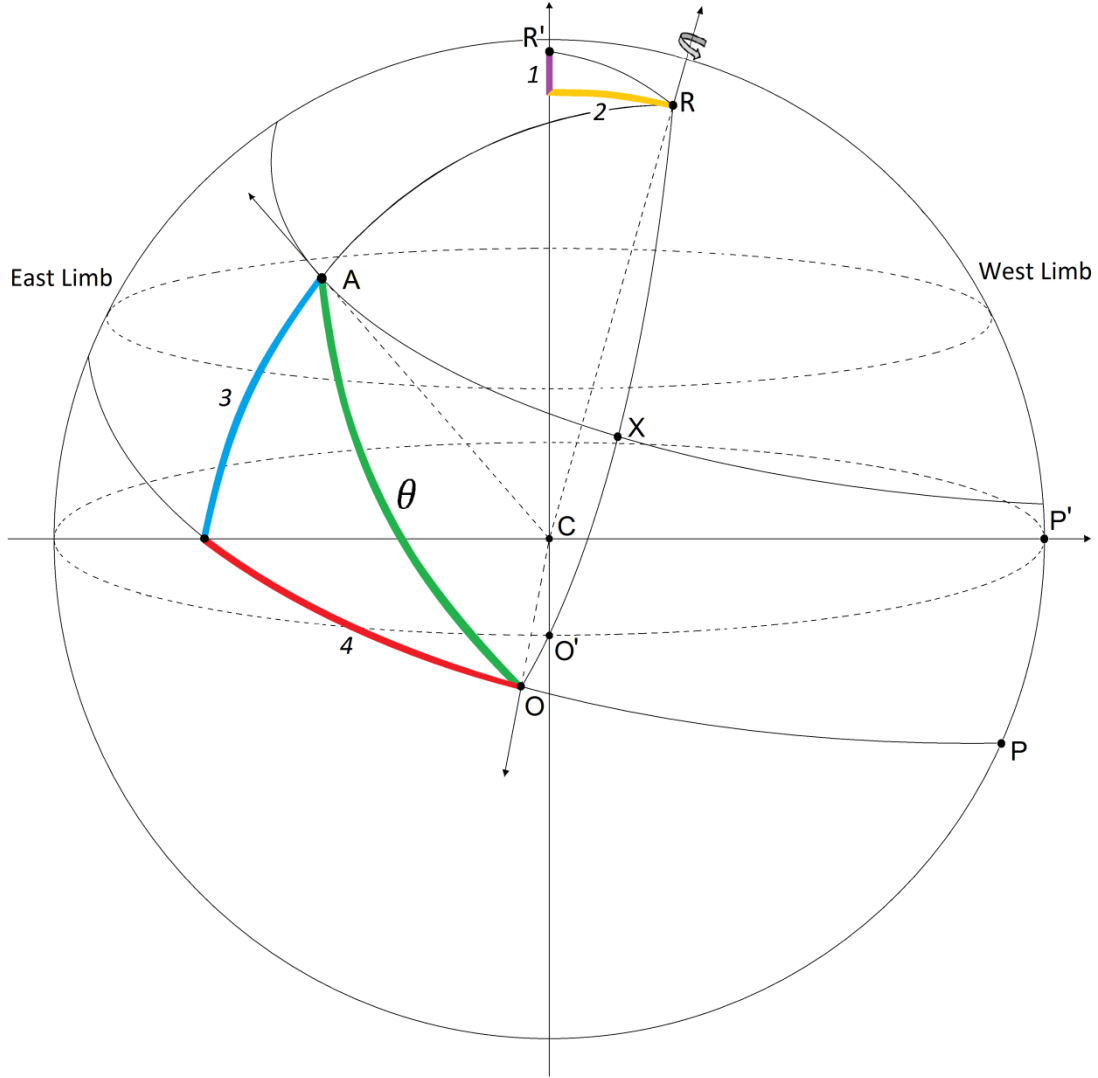


Figure 4. Solar Coordinate System. CR' denotes the line through the celestial north pole of the Sun. CR denotes the rotational axis of the Sun. The angle subtended by 1 is the B angle while 2 denotes the P angle. A represents the position of a feature on the solar surface with latitude subtended by 3 and longitude subtended by 4 in heliographic coordinates.

2.7 Solar Coordinate Systems

Solar coordinates, or heliographic coordinates, are defined in much the same manner as Earth coordinate systems, utilizing latitude and longitude to describe locations on the surface of the respective spherical body. For the purpose of this research, latitude is defined as degrees north or south of the solar equatorial plane, the plane defined by arc $O-P$ in Figure 4. Note that the solar equator does not lie on the ecliptic plane which is defined by arc $O'-P'$ in Figure 4. For reference, the line through points C and O' traces directly toward an observer at Earth including the SDO satellite. As a consequence, point O' is the apparent center of the solar disk. However, point O lying on the solar equator defines zero degrees latitude. The B and P angle help to define the orientation of the ecliptic plane to the solar equator allowing for conversion between the apparent locations of solar features on the solar disk to their location in heliographic degrees.

A principal distinction for solar coordinate systems needs to be made in regards to longitude calculation. There are two primary methods of recording the longitude of solar features. This first is called the Stonyhurst longitude. Simply put, this method measures degrees east or west of a central meridian that is defined through points O and R in Figure 4 (Thompson, 2006). In this way, a feature located at point O on the solar surface would have a Stonyhurst longitude of zero degrees. The alternate method is through use of the Carrington longitude. The Carrington longitude rotates with the Sun implying that its apparent orientation from an Earth observer is constantly changing. Zero degrees Carrington longitude is defined by the meridian passing through an arbitrarily picked reference point by Richard C. Carrington (Thompson, 2006). This point is tracked at a standard rotational rate, making one full rotation with the Sun every 27 days. Carrington longitude is measured $0^\circ - 360^\circ$, starting at the reference point and increasing to the west. The Carrington approach is useful for solar observations that do not coincide with the Earth's view of the Sun. For instance, during the application of the automated sunspot

classification code of Spahr (2014) to SOHO imagery, Howard (2015) needed to employ the Carrington system of longitude measurement since the SOHO satellite is not located in a “near” Earth orbit resulting in a different relative appearance of the Sun.

From time to time both the Stonyhurst system and Carrington system are referred to as the heliographic coordinate system. However, for the purposes of this research any reference to degrees longitude or heliographic degrees longitude will explicitly refer to the Stonyhurst measuring system. Latitude is measured in the same manner by both systems. Note that the research code described in detail later in this document utilizes decimal degrees latitude and longitude to the hundredths place for location determination and refrains from use of the degrees-minutes-seconds nomenclature.

2.8 Approach to Automated Detection and Tracking

Discrepancies in sunspot classification between solar observatories and nationally and internationally published sunspot reports are often not small. These differences can be attributed to several causes to include sunspot observations taking place at different times of day and application of diverse solar imagery. Additionally, direct human involvement in the classification process undoubtedly increases the subjectivity in sunspot characterization, adding extra inconsistency in the classification process. The purpose of this research is to provide a purely objective process for sunspot characterization that removes human bias and adds a higher level of consistency through an automated detection, classification, and tracking code.

In any automated process, the solar active region, or sunspots in particular, must first be detected. Most automated detection algorithms follow a similar process of preprocessing and thresholding an image to identify sunspot features and then building that region through morphological and region growing techniques (Benkhalil et al., 2004; Watson and Fletcher, 2010; Watson, 2012; Qahwaji and Colak, 2005; Zharkov et al., 2005). There is a large degree of flexibility in the application of these processing

techniques depending on the priorities of the research. The primary tradeoff when picking feature detection methods is run time of the algorithm versus accuracy and consistency of the detected object (Watson, 2012). Spahr (2014) utilized an iterative thresholding and region building method that takes several minutes to examine a single image. Though this is considered a “long” time period when compared to other detection methods, the code does exhibit a high degree of consistency in detection and classification. Of note, the objective of the Spahr code was never to match human classification schemes or replace existing observing methods. Rather, his focus, and that of this continued research, is to make as accurate a sunspot classification as possible given a strict interpretation of the McIntosh classification system. As such, so called machine-learning techniques, as utilized by several automated detection methods (Qahwaji and Colak, 2006), have been disregarded for this research as they seek to match human tendencies. Nevertheless, these methods have shown utility for other researchers and research objectives.

Prior work by Spahr (2014) and Howard (2015) did not include a feature tracking algorithm. They focused on feature detection for a single point in time. As stated above, feature detection and automated classification has seen a high volume of research, but such topics rarely include automated feature tracking. Time evolution of sunspots, and consequently the time dependent magnetic makeup of the photosphere, can only be studied with consistent identification of a single feature over the course of several solar images taken at reasonably small time intervals. As a rare example, Watson (2012) used a simple and effective method for feature tracking. In his algorithm, solar rotation is determined based on the latitude of the identified feature using the equation

$$\omega(\varphi) = A + B\sin^2(\varphi) + C\sin^4(\varphi) \quad (3)$$

$$A = 2.894 \pm 0.011$$

$$B = -0.428 \pm 0.070$$

$$C = -0.307 \pm 0.077$$

where ω is the rotation rate of the sun in $\mu rad\ s^{-1}$ at latitude φ (Howard et al.,1990).

The latitude dependence of this equation corrects for the differential rotation of the sun as described in Section 2.1. Watson then compares features from two images using the time difference between each image and the calculated solar rotation rate to determine where the feature should have progressed. If the feature on the second image is located where the feature from the first image should have moved, within a tolerance, the two regions are identified as the same feature. The changing shape of a sunspot with time can result in an apparent acceleration of the sunspot movement due to the morphing location of the spot centroid. A tolerance must be picked that can correct for this erratic centroid movement, but still allow for detection of nearby, distinct sunspots or sunspot groups (Watson, 2012). This research will apply a similar algorithm for feature tracking to the existing detection and classification MATLAB code.

III. Methodology

This chapter describes the capabilities and processes present in Spahr’s sunspot detection and classification code for SDO imagery. Each stage of the existing code will be covered along with adjustments made for this research in order to analyze an additional two years of solar images. Note that certain tools utilized and described by the Spahr code are well established image processing techniques and, therefore, are not necessarily described in great detail. Additionally, this chapter will describe steps taken to add a sunspot tracking algorithm and Mount Wilson magnetic classification algorithm to the existing code. The decision making behind the algorithm is discussed here, but discussions concerning the performance of the tracking algorithm, magnetic class algorithm, and existing Spahr code will be left to Chapter IV.

Before getting into the details of the code, the reader should note the treatment of digital images by the MATLAB computational software. Digital images are comprised of a set number of pixels, each containing unique information about the physical object being represented by the image. In this way, the digital image is really just a matrix of data points, with each element uniquely identified by a row and column number. Consequently, the terms ‘image’ and ‘matrix’ at times are used interchangeably in the descriptions below.

3.1 Image Acquisition

As discussed previously, this research utilizes imagery from NASA’s SDO project. SDO solar imagery is available in various spatial resolution formats, but this project utilizes the highest resolution imagery available, 4096×4096 pixels. Both HMIIC and HMIB images for the time period spanning 1 July 2013 through 31 July 2015 were downloaded from the SDO archive webpage, available at <http://sdo.gsfc.nasa.gov/assets/img/browse/>. The archive makes HMIIC and HMIB

images available at fifteen minute intervals. All images are used courtesy of NASA/SDO and the AIA, EVE, and HMI science teams. These images were downloaded in JPEG format using a consistent naming convention that included the valid date and time of the image. The detection and classification code described later in this chapter relies on the condition that both HMIIC and HMIB images are valid for the same time period and have the same spatial resolution. Of note, colored intensitygram images were used for ease with visual confirmation of detected regions. However, the HMIIC image is converted to grayscale early in code execution, and colorized images are not necessary for a successful code run. Grayscale intensitygram images could be incorporated into future editions of this code and may be more practical due to their reduced file size over colored images.

3.2 Feature Detection

3.2.1 Solar Ephemeris

Each observer of the Sun sees a slightly different image due to the variations in season and viewing angle. These differences cause ambiguity in determining the true location of a sunspot on the solar surface. For example, a solar observatory located on Earth's surface will have a different perspective of the Sun than the SDO satellite situated in an Earth orbit thirty-five thousand kilometers above the ground with near constant view of the sun. Additionally, both observing stations notice an apparent change in orientation of the solar disk over the course of a year due to the offset between the solar rotational axis and the ecliptic plane. In order to correct for these viewing differences of the solar disk, certain parameters must be extracted from the solar ephemeris, a common astronomical tool for calculating approximate positions of orbiting bodies (Seidelmann and Urban, 2013). Spahr (2014) used the framework of Wilson (1980) and Meeus (1982) to construct an ephemeris algorithm for use with SDO images.

The solar ephemeris algorithm first converts the valid time of each image into its Julian Date which allows for application of known solar and planetary positions

(Seidelmann and Urban, 2013). The three parameters calculated within, and then extracted from, the algorithm are the B angle, the diameter of the Sun in radians, and an estimation of the radius of the Sun as seen from the SDO satellite in pixels. Additional parameters are calculated within the ephemeris algorithm but are not explicitly needed for further detection and classification computation. These include the P angle of the Sun, which is corrected automatically by SDO image processing (Pesnell et al., 2012; Schou et al., 2012; Scherrer et al., 2012), and the parameters of the orbit of SDO about the Sun to include longitude of perihelion, mean anomaly, eccentricity, and the right ascension of the ascending node.

The B angle, as seen in Figure 4, is the tilt of the solar north pole toward or away from the observer (Seidelmann and Urban, 2013), and is critical in defining the location of zero degrees longitude and latitude. For instance, if the B angle is calculated to be zero, longitude and latitude are both zero at the center of the solar disk, but a non-zero B angle implies that zero degrees latitude will move north or south of the center of the solar disk as seen by the observer. Consistent application of the B and P angle are vital in the correct assignment of sunspot, or other solar feature, position in degrees longitude and latitude across the various solar observing entities. The diameter of the Sun in radians is extracted from the algorithm and is based upon the known position of the Earth and Sun for a given Julian Date. The approximate radius of the Sun in pixels is also calculated using an approximation for the Sun-Earth distance in meters found in the ephemeris. To do so, an experimental constant of proportionality determined by Spahr (2014) to be 2.8476×10^{14} *pixel meters* is divided by the Sun-Earth distance giving the pixel radius. This approximate radius is used later as a first guess for the edge detection algorithm to speed up the computation time. Note that this constant of proportionality was derived for the 4096×4096 pixel SDO image and will need to be adjusted if additional image sources or different resolution images are to be used with this automated classification code.

3.2.2 Edge Detection

In order to determine the location of any feature on the solar surface, the code must first determine the extent of the Sun by determining the edge of the solar disk. Spahr (2014) accomplished this through the use of image processing techniques available in MATLAB. The edge detection algorithm first detects all possible edges on the HMIIC image using a Canny edge definition technique (Gonzalez and Eddins, 2009). Other edge detection methods were available, but Spahr decided the Canny method proved the most reliable for large intensity images. These methods incorporate a Gaussian smoothing filter, often referred to as sigma or σ . A large sigma will increase the likelihood of detecting certain edges but also results in increased ambiguity in the exact location of those edges (Gonzalez and Eddins, 2009). Spahr tested several different sigmas and determined that $\sigma = 3$ proved the most reliable for accurately determining the edge of the Sun. An example output image of the Canny edge detection is seen in Figure 5. This image is a binary image with white shaded regions depicting identified intensity gradients as possible edges. The algorithm then takes the Canny image and applies a MATLAB circle finding function. Instead of finding all circles on the image however, the code limits the search for circles to a pixel radius $\pm 1\%$ of the estimated solar radius from the ephemeris calculation. The result is a reliable circle defining the edge of the solar disk as seen in Figure 5. The circle finding function then outputs the center and radius of the circle, which are recorded as the center and radius of the Sun in pixel space. It is understood that the Sun is not a perfect circle. However, a circle approximation is correct to an acceptable margin. If no edge, and therefore no circle, is found near the estimated solar radius, the algorithm will increase the sigma value by one step size and re-run the edge detection algorithm. As mentioned above, the larger sigma increases the likelihood of detection but will also add more ambiguity to the edge definition. This ultimately

results in a slightly less accurate solar radius calculation. Spahr (2014) corrected for this possible inaccuracy by adding a factor of $\sqrt{\frac{\sigma}{3}}$ to the calculated radius in pixels.

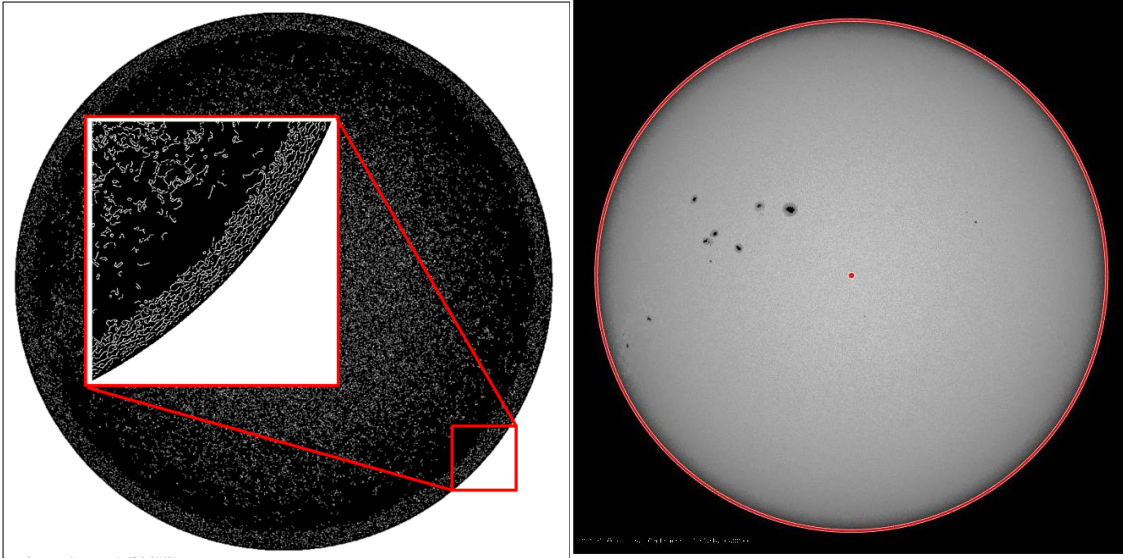


Figure 5. Canny Edge Detection and Solar Radius Determination. In the left image, Canny edge detection is applied to the grayscale intensity image producing a binary image with small white lines depicting identified intensity gradients. The **imfindcircles** MATLAB command searches the canny image for a completed circle of these intensity gradients in proximity of the estimated solar radius. The identified circle is the edge of the solar disk and **imfindcircles** outputs the radius and center of the Sun, identified in red on the right image.

3.2.3 Limb Darkening Correction

The limb darkening effect described in section 2.5.1 must now be corrected. In order to do so, the code generates an inverse intensity image, or negative image, of the quiet Sun and adds that inverse image to the grayscale intensity image being analyzed. The term ‘quiet Sun’ refers to a period when there are no active regions or sunspots visible on an intensity image of the Sun. In essence, it is a control image for analysis of more complex intensity images. By adding the inverse quiet Sun image to the image being processed, the darkened limb of the Sun and the center of the solar disk are both

corrected to an average intensity value, while active regions and sunspot groups remain identifiable since the inverse image did not contain those features. The result is a ‘flattened’ intensity image.

The process for creating the inverse quiet Sun image in the code is described as the Eddington approximation for mapping the limb darkened Sun (Foukal, 2008). This approximation is adapted into the relation

$$I = 1 - \frac{1 + \sqrt{3}\mu}{1 + \sqrt{3}} \quad (4)$$

where I is the apparent intensity due to limb darkening for the inverse image and μ is the cosine of the angle, θ , between the center of the Sun and the location on the solar surface being corrected for limb darkening (Foukal, 2008). Note that this θ is the same as that seen in Figure 4 if point A were the location of interest. A matrix with the same dimensions as the intensity image is assigned values of one at all points that fall within the Sun in pixel space as defined by the center of the Sun and solar radius from the edge finding algorithm. Equation 4 is then applied to this matrix and the result is an inverse image with values at each point falling between zero and one. For example, the matrix element corresponding to the center of the solar disk has an intensity value of zero since $\mu = 0$, and elements corresponding to 45° off center are assigned an intensity of 0.186. The inverse quiet Sun image is added to the grayscale intensitygram image being analyzed. The result is a flattened intensity image that will be used for feature detection. An example of this flattened image is given in Figure 6.

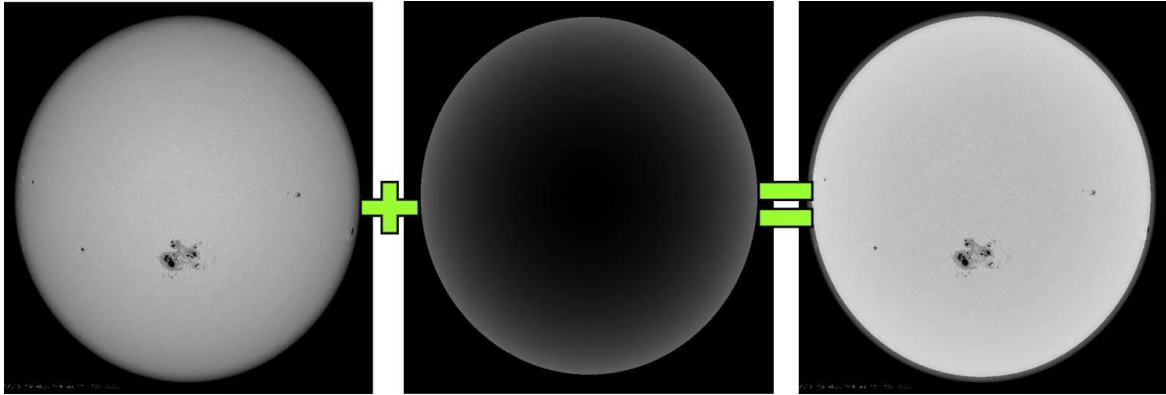


Figure 6. Limb Darkening Correction. The left image is the original grayscale intensity image. An inverse quiet Sun image (center) is created and added to the original intensity image to correct for limb darkening effects. The result is a flattened intensity image on the right. Note the brighter limbs of the flattened image.

3.2.4 Thresholding

This section describes the techniques by which automated sunspot detection algorithms, and this research code in particular, detect solar features and recognize them as individual sunspots. As mentioned in Section 2.8, many methods for solar feature detection have been explored. A notable class of detection is referred to as region growing through morphological reconstruction (Aschwanden, 2010; Watson and Fletcher, 2010; Watson, 2012). Morphological reconstruction is a nonlinear image processing technique that recognizes shapes on a digital image through use of structuring elements that can be any shape desired. Often crosses, circles, or squares are employed depending on the needs of the researcher (Watson, 2012). These algorithms fit the structuring element into initially identified features and then grow the structuring elements pixel by pixel until the structure element reaches a pixel at a certain intensity threshold. The resulting grown structure is the detected sunspot. There are a few notable disadvantages to this method of detection. First, use of nonlinear processes in the reconstruction alters the data in the intensity image in an unrecoverable way (Gonzalez and Eddins, 2009). This potentially reduces availability of the original data for later

analysis. Additionally, the ability of the algorithm to detect features is entirely dependent on the structuring element utilized. If the structuring element does not fit a given solar feature, either due to size or shape, then that feature will not be identified. This has led to many implementations of this detection technique failing at detection of small sunspots (Colak and Qahwaji, 2005; Zharkov, 2007; Watson, 2012).

In order to avoid these potential negative effects, Spahr decided to use an iterative thresholding technique that avoids use of the structuring element. The first step of the thresholding algorithm is to take the limb darkening corrected image, or flattened image, and invert intensity values so that sunspots and their umbra and penumbra appear bright rather than dark. Next, the code takes the inverse flattened image and converts it to a binary image using an initial threshold value of 0.4. All intensity values in the inverted image greater than 40% of the maximum intensity value are assigned a value of one (white) to indicate sunspots. All other points on the image are given a value of zero (black). In this way, all pixels on the inverted flattened image that have intensity values above the threshold are associated with sunspots. The pixels do not need to fit a size or shape as in morphological reconstruction, so the possibility of missing small sunspots early on in the detection process is reduced. However, it should be noted that this thresholding technique comes with its own disadvantages. Namely, this method is susceptible to recognizing noise and granulation on the solar surface as sunspots due to the fact that the code is not looking for a particular shape. It is only looking for pixels above a certain intensity value (Curto et al., 2008). This research is fortunate to be using SDO intensity images that, having only been operating since 2010, do not experience as much image noise as other legacy solar observing satellites such as SOHO. Howard (2015) ran into this problem with application of this code to SOHO/MDI imagery. Readers are encouraged to refer to her thesis for details on corrective measures.

The next step in the thresholding algorithm is to identify all white pixels that are associated with the same sunspot. The algorithm calls on the **bwlabel** MATLAB

command to identify all white pixels adjacent to one another as the same feature, with each pixel within the feature then given the same identification number (Gonzalez and Eddins, 2009). The command then completes the same process for all white pixels on the image, identifying connected features as appropriate and assigning the next appropriate identification number to each group of connected pixels. Figure 7 demonstrates this process. The two outputs for the **bwlabel** command are a matrix with each sunspot region labeled with its unique identification number, referred to as the labeled matrix, and the number of connected features, in this case representing the total number of sunspots on the image.

To this point, a single threshold value of 0.4 has been used to test sunspot detection. In reality this threshold value is fairly large and usually results in few sunspots detected. The thresholding algorithm now decreases the threshold value by a large increment at first. The **bwlabel** command is run again to identify connected features and outputs the number of detected sunspots. This number of sunspots is compared to the number of spots for the initial threshold value. If the growth of spots is less than a set expansion rate, the threshold value is dropped again by the same increment and the **bwlabel** command runs another time. This manner of dropping the threshold by the same increment and reevaluating is continued until the growth of sunspots between runs increases rapidly, indicating that this threshold value is now allowing for detection of noise and other features that are not sunspots. At this point, the threshold value is assigned its previous value and then dropped at an increment that is a factor of ten smaller than the previous increment. In addition, the acceptable growth rate is reduced at this point in order to hone in on the appropriate number of sunspots. Connected features are identified again and the threshold value is decreased at the new increment as necessary. This iterative process will continue until the increment drop in threshold value is reduced to 10^{-4} . The smallest acceptable threshold value at this increment is then applied to the flattened intensity image and the resulting black and white image

displaying sunspots with connected features, also known as the labeled matrix, now depicts all detected sunspots for use in the next steps of the code.

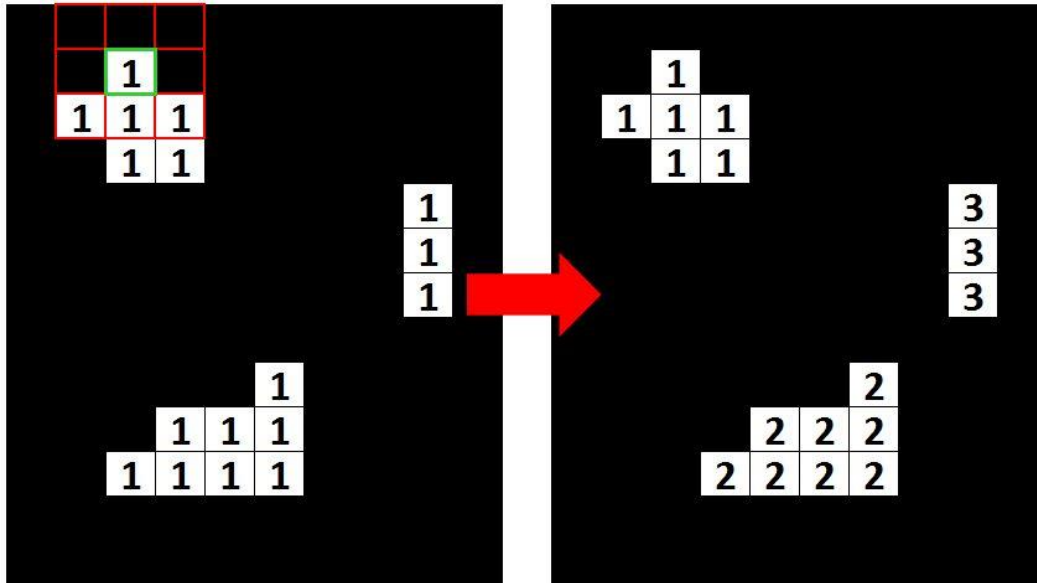


Figure 7. Identification of Connected Elements. A binary image (left) is created from the grayscale intensity image with all pixels above a certain threshold value identified by the color white. The **bwlabel** MATLAB command cycles through each white pixel and identifies adjacent white pixels as part of a connected element. The output binary image (right) assigns each connected element a unique identification number, creating a labeled matrix representing the entire solar disk. The code recognizes the number of connected elements as the number of sunspots.

As stated in Section 2.2, the darkest part of a sunspot is called the umbra, and many mature sunspots also include a slightly brighter penumbra that partially or completely surrounds the umbra. Umbrae and penumbrae both generally stand out well against the rest of the solar surface on intensitygrams, but the thresholding process described above has so far identified them as the same feature. The next step of the thresholding algorithm distinguishes between umbrae and penumbrae. Typical intensity values for penumbra regions are found to be 35% that of the surrounding solar surface while umbra intensity values average 15% (Foukal, 2008). Therefore, the umbral regions

can be identified as 20% darker than any associated penumbra. The algorithm now applies the thresholding method again to the black and white intensity image, but this time with a threshold value 0.2 times higher than the threshold value settled on above. The resulting black and white image depicts all umbra regions white while penumbra and the solar background are depicted as black. This umbra map is held separate from the labeled matrix, which still contains information about regions of penumbra. The final step in the thresholding algorithm is to take the HMIB image and convert it to a binary image with regions of magnetic field (inward directed and outward directed) assigned a value of one and all other areas given a value of zero. This new magnetogram binary image is multiplied into the labeled matrix from above. The result is the finalized labeled matrix that only identifies sunspots that are co-located with areas of non-zero magnetic field on the solar surface. As stated in section 2.2, sunspots are well known to be manifestations of magnetic field in the photosphere so performing this last check reduces the chance of identifying non-sunspot features in the labeled matrix.

3.3 Group Definition

With each sunspot having now been detected and numbered, the code begins the determination as to whether or not individual sunspots belong to a group or if they are to be classified alone. The group definition algorithm performs another iterative looping scheme to test each identified sunspot against all other spots for separation distance and magnetic polarity. The grouping criteria used in this research code and described further below matches that put forth by Patrick McIntosh (McIntosh, 1990) and is the same as that used by USAF solar observers for manual classification as stated in AFMAN 15-124 and AFWAMAN 15-1.

3.3.1 Distance Determination

The first criterion for group classification is the distance between spots in heliographic degrees. In order to calculate this distance, the location of detected sunspots from the labeled matrix must be converted from x-y pixel space to heliographic coordinates. Spahr (2014) created a MATLAB function to perform this task that reads in the position of the feature in pixel space, the B angle of the Sun for the valid time of the image being analyzed, and the center and radius of the Sun calculated in the edge detection algorithm. The output of this function is the heliographic latitude and longitude of the sunspot in question. The code then calculates the distance between each sunspot using the following equation.

$$distance = \sqrt{(Long_{spot1} - Long_{spot2})^2 + 4(Lat_{spot1} - Lat_{spot2})^2} \quad (5)$$

This equation is a typical calculation of displacement except for the factor of 4 placed on the right side of the equation under the radical. This value magnifies the north-south displacement of the two spots being compared, thereby increasing the calculated distance between the two spots. The result is that spots with larger latitude displacements will be less likely to have separation distances that fall within certain criteria for the grouping scheme. This is done because sunspot groups generally span left to right due to the rotation of the solar plasma (Foukal, 2008). Some north-south separation is expected, as seen by the prevalence of leading spots existing slightly more equatorward than trailing spots, but will generally be much less than the east-west span. The distance correction applied above ensures that the grouping scheme favors the east-west span of sunspot displacements when determining whether two spots belong in the same sunspot group. Manual observers are trained to account for the expected orientation of sunspot groups, so in a sense, this correction accounts for the inability of the code to learn human bias.

3.3.2 Magnetic Polarity Determination

The other McIntosh criterion for sunspot grouping is the magnetic polarity of each detected sunspot (McIntosh, 1990). In order to determine magnetic polarity the grouping algorithm creates a logical matrix with values of one assigned to all pixel locations corresponding to the sunspot in question and then multiplies that matrix with the HMIB Magnetogram image. The result is a matrix containing magnetic field information only for the matrix elements, or pixels, corresponding to the sunspots. All other pixels on the image have a value of zero. As mentioned in Section 2.4.2, white pixels on the magnetogram denote outward directed magnetic field while black pixels denote an inward directed magnetic field. For reference, MATLAB assigns a numeric value to all colors, with 205.5 assigned to the color white and a value of 50 assigned to the color black. Next, the code averages all the magnetic values for pixels corresponding to the sunspot being analyzed. If the average is greater than 127.5, or greater than halfway between the two color values, then the spot is labeled as having a polarity of 2 which corresponds to the color white on the HMIB image. Likewise, an average polarity value below 127.5 is assigned a polarity of 1 which corresponds to the color black on the magnetogram. There are cases when the same sunspot contains both magnetic polarities within the same penumbra. In this case, the grouping code would assign the entire sunspot the predominant polarity. This does not negatively affect the Spahr code execution. However, the Delta (δ) classification from the Mount Wilson Magnetic classification scheme represents this precise scenario, when the same penumbra contains both magnetic polarities. The Mount Wilson Classification system was not previously incorporated into this research code but is being added for this rendition. As such, the Mount Wilson magnetic classification algorithm to be discussed in Section 3.6 will reanalyze each sunspot for the presence of opposite polarity umbrae within the same penumbra.

3.3.3 Grouping Length

The grouping length described in this section will be used as a test for whether or not individual spots should be assigned as members of the same sunspot group. Please note that this parameter is not the same as sunspot group length, a parameter often available on sunspot observation bulletins from SWPC and other sources, which will be calculated a bit later in this project. The need for this calculation of grouping length arises out of the fact that the code has no initial sense of the sunspot group to be formed. A group starts as a single spot and then iteratively grows as more spots are added. As a result, the centroid of the group is constantly changing and comparison of this centroid to other sunspots for inclusion into the group will therefore be inconsistent over the course of the new sunspot group's evolution. This is different in a sense from manual observation where the observer will have a good idea of the sunspot group shape and size from the start due to visual inspection. To account for this difference in automated classification, Spahr (2014) developed a grouping length calculator that incorporates ten years worth of manual sunspot observations from four different sources (three different USAF solar observatories and SWPC). Spahr realized that the successful grouping of spots is highly dependent on an initial assumption for the length of the group. For instance, certain sunspot groups may be formed more correctly if the grouping length used to test for inclusion was set to 10 degrees rather than 15 degrees. Other groups will perform better with a different first assumption, often with more complex spots and spot groups needing a larger grouping length for accurate assimilation. The grouping length calculation described below allows for application of the most appropriate grouping length rather than trying to fit all groups to the same length, which would inevitably create a large amount of error.

The parameter to be analyzed in order to pick the most appropriate grouping length will be the combined area, in millionths of a solar hemisphere (MoSH), of the

sunspots being analyzed for inclusion into a group. Spots that have a larger area are assigned a larger grouping length for testing and vice versa. The calculator itself is derived by comparing the length and area of sunspot groups from the ten years of manual data. Spahr (2014) created two relations, the first trial comparing the maximum group length from the four sources to sunspot area and the second trial compared the average group length to sunspot area. Equations for each of these two relations were derived from the data and are included below.

$$\text{Trial \#1: } Length = 8.276 \frac{Area^{0.2276}}{10} - 2.875 \quad (6)$$

$$\text{Trial \#2: } Length = -24.74 \frac{Area^{-0.08423}}{10} + 32.96 \quad (7)$$

The third and final relation is a linear interpolation of values lying between the two equations above. This interpolation is now used to find the expected grouping length of a sunspot group given a combined value for sunspot area. This calculation favors toward slightly longer group lengths in order to ensure no exclusion of sunspots in the grouping scheme.

With the above calculation in place, the area of the identified sunspots must be calculated in order to obtain the appropriate grouping length. A simple ratio of pixels contained in each sunspot to the total number of pixels on the disk of the sun gives the relative size of the sunspot to the solar disk. This value is then multiplied by 1×10^6 to put the value in millionths of a solar hemisphere and finally divided by the cosine of the angle of the sunspot off the center of the solar disk, which is the same μ from equation 4 from Section 3.2.3, since objects near the limb of the Sun appear smaller than objects toward the center of the solar disk. The combined equation for the area calculation is given as

$$Area = \frac{A}{2\pi r^2} \frac{1 \times 10^6}{\mu} \quad (8)$$

where A is the number of pixels contained by the analyzed sunspot and r is the radius of the sun in pixels from the edge detection algorithm.

3.3.4 Group Assignment

The code is now ready to call on the grouping length calculator for group assignments. The algorithm sorts all sunspots identified in the labeled matrix from the thresholding routine from largest to smallest, and then tests each sunspot against every other sunspot using three looping structures. The first loop is to determine whether or not the sunspot to be analyzed has already been assigned a group. If not, the sunspot is processed through a second loop in the algorithm where any sunspots that are within five degrees of a test spot are assigned to the same group. If spots with opposite magnetic polarity exist within that five degree limit, a third loop is initiated. Within the third loop, the grouping length calculator described in Section 3.3.3 is called on with the total area of spots already identified in the group used to determine the grouping length. The sunspots are tested from largest to smallest to ensure intermediate area calculations are maximized and, therefore, the grouping length calculated will be maximized for greater inclusion of spots in the group. This is done to minimize the chances of missing sunspots that should be grouped together. With the grouping length determined, another round of testing is accomplished for all spots falling within the grouping length measurement. Finally, sunspots that do not meet the criteria above are assigned as their own sunspot group. Throughout this process a new labeled matrix is formed, this time with all sunspots within the same group given the same identification number. Additionally, a sunspot group is labeled as bipolar if there are sunspots with opposite magnetic polarities in the same group. Likewise sunspot groups with all spots having the same magnetic polarity, or spots that are grouped alone, are given a unipolar classification. This simple magnetic classification is needed for the McIntosh classification of sunspot groups coming up next.

3.4 Feature Extraction

Prior to application of the McIntosh classification system, a final round of processing needs to take place. This encompasses the use of the MATLAB data representation function titled **regionprops** (Gonzalez and Eddins, 2009). This MATLAB function extracts and calculates key features from the labeled matrix of sunspot groups, including sunspot group length, length of largest sunspot penumbra, eccentricity of the largest sunspot, area of the sunspot group, the completeness of the penumbra, and the spread of sunspots within the group (Spahr, 2014). Area and group length have been calculated prior, but those calculations were not necessarily taken from the finalized sunspot grouping. The code has now compiled the necessary parameters for McIntosh classification. The rest of this section is dedicated toward that end. It is important to note that certain McIntosh classification parameters are strictly defined while the descriptions for other parameters can be a little vague, in which case logical interpretation is necessary. Each of the three McIntosh classifications tiers are described independently below with any presumptions in analysis identified.

3.4.1 Zurich Classification

The Zurich classification is the first tier, or first letter, of the 3-letter McIntosh classification as described in Section 2.3.1. The primary parameters analyzed here are the length of the sunspot group and completeness of the penumbra surrounding the leading and trailing spots (McIntosh). The decision tree for Zurich classification is given in Figure 8. As described earlier in this chapter, penumbrae are distinguished from umbrae based upon the intensity of the pixels on the HMIIC image being analyzed. With this distinction available, the Zurich classification algorithm first tests for groups that will receive the ‘A’ or ‘H’ classification. Both require a unipolar magnetic structure. The difference lies in the presence of penumbra. Unipolar groups with no penumbra are classified ‘A’ while groups with penumbra are given a classification of ‘H’. However,

due to the very high resolution of SDO images and automatic CCD binning of photons incident on the SDO camera, pixels meeting the penumbra threshold almost always partially surround dark pixels identified as umbra, and, as a result, no ‘A’ classifications would be given. This is a limitation of using digital imagery since this appearance of penumbra in these cases does not necessarily exist on the Sun. A correction is applied by utilizing a minimum area threshold for ‘H’ classifications in the algorithm so that the ‘A’ classification is given to the smallest unipolar groups with area less than five MoSH. This is a correction not explicitly called for by the McIntosh system, but is ultimately necessary for a proper functioning automated code (McIntosh, 1990). Additionally, this change makes some physical sense, as groups classified as ‘H’ are understood to be more developed groups at an advanced stage of a sunspot’s lifespan than ‘A’ groups (Foukal, 2008), and ‘H’ groups should therefore maintain a larger extent.

Bipolar groups are now classified by the Zurich classification algorithm. ‘B’ classifications are given to bipolar groups that do not possess any identified penumbrae, though again the presence of penumbra cannot strictly be enforced for the same reasons stated above. To correct for this, the code identifies ‘mature’ spots, or those spots whose umbral area is less than 85% of the total spot area. Penumbra is the most common characteristic of a fully developed sunspot (Foukal, 2008). Spahr experimentally developed this threshold to distinguish between ‘B’ classifications and the other more developed bipolar spot groups, meaning that ‘B’ groups are not identified as having ‘mature’ sunspots. Again, this is a slight, but necessary, addition to the McIntosh classification system in order to allow for proper code execution. Continuing on, any spots with a single ‘mature’ spot are given the ‘C’ classification, and groups that have ‘mature’ leading and trailing spots are further classified into ‘D’, ‘E’, and ‘F’ depending on the length of the group as illustrated in Figure 8.

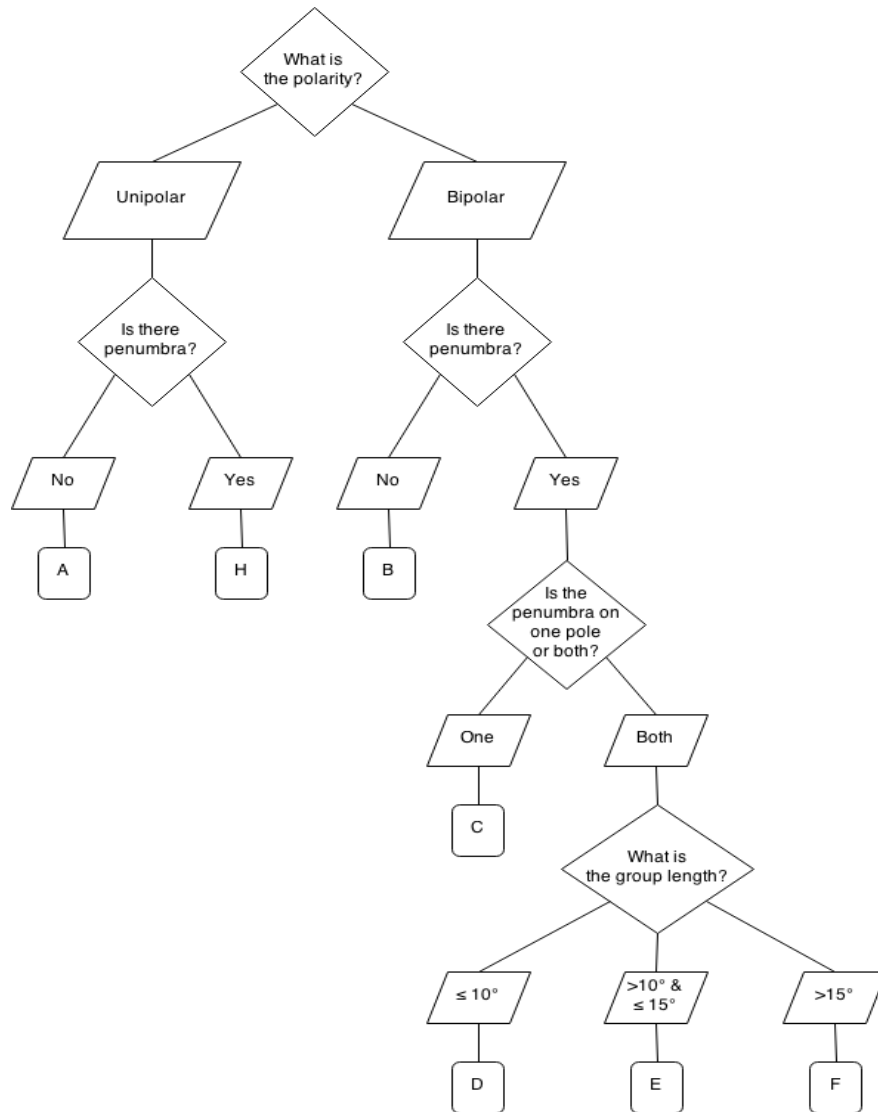


Figure 8. Zurich Classification Decision Tree. Adapted from Howard (2015).

3.4.2 Penumbra Classification

The next tier in the McIntosh classification system more strictly classifies the penumbra of the largest spot, usually the leading spot, in the sunspot group (McIntosh, 1990). The penumbra class of ‘x’ is given to groups that contain no penumbra, and therefore will correspond to Zurich classes ‘A’ and ‘B’. The next penumbra class of ‘r’ is designated for spots with rudimentary penumbra that partially surrounds the largest spot in the group. Spahr (2014) defined this class by first identifying the largest spot of the

sunspot group. Then the area of the umbra of that spot is divided by the total area of the spot. If the ratio is greater than .5, or the umbra is over half the size of the whole spot, the penumbra associated with this spot is considered rudimentary, and the spot is assigned the penumbra class 'r'. Spots that have an umbra less than 50% of the total spot area are mature spots and are further classified below. It is important to note that the term 'mature' means two different things between this section and section 3.4.1. During the Zurich classification of the previous section, the 'mature' designation was only used because the code likely cannot identify spots with no penumbra due to binning of intensity values. In this section, the mature threshold delineates between two different classifications that both have penumbra present.

Four separate penumbra classifications are left available for mature sunspots, or well developed sunspots with significant penumbra, and each is distinguished by the eccentricity and length of largest spot in the sunspot group. Eccentricity is again calculated using the **regionprops** MATLAB command (Gonzalez and Eddins, 2009), this time only applying the function to a single spot rather than the entire group. Eccentricity values of zero imply a circular object while a straight line would receive an eccentricity value of one. The code interprets an eccentricity value less than 0.5 as symmetric while values greater than 0.5 are considered asymmetric. Length is determined by finding the extreme pixels on the spot, converting from pixel space to heliographic degrees, and then determining displacement between those two points. An asymmetric spot with penumbra length less than 2.5 degrees is assigned the penumbra class of 'a' while a symmetric spot less than 2.5 degrees in length is assigned the 's' class. An asymmetric spot with penumbra length greater than 2.5 degrees is assigned the class of 'k' and, finally, a symmetric spot with penumbra length greater than 2.5 degrees is assigned the penumbra class of 'h'. Figure 9 presents this decision process.

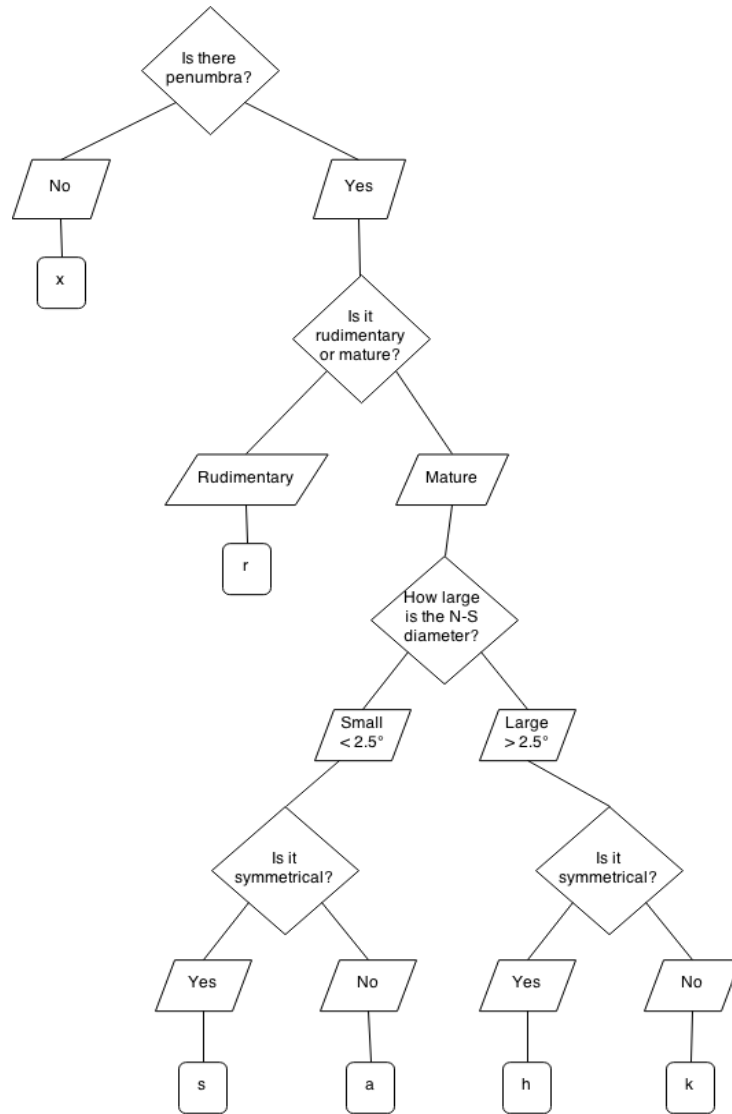


Figure 9. Penumbra Classification Decision Tree. Adapted from Howard (2015).

3.4.3 Compactness Classification

The final tier of the McIntosh classification system further analyzes the compactness of, or distribution of sunspots within, the sunspot group (McIntosh, 1990). The first class, ‘x’, is given to all unipolar sunspot groups (‘A’ and ‘H’ first letter classifications). Three different classes are available for bipolar sunspot groups. Due to the ambiguity in the language used to describe these three classes, Spahr (2014) created what he considered reasonable threshold values between each class. The compact class,

‘c’, is given to the most complex bipolar groups. The criteria determined for this class include greater than five spots between the leading and trailing spot, mature spots with well defined penumbra at both the leading and trailing position, and the presence of mature penumbra on at least one sunspot between the lead and trailing spots. This implies that this class can only be applied to Zurich classes ‘D’, ‘E’, and ‘F’. To further define the ‘c’ class, Spahr (2014) includes a length requirement. In practice, small narrow sunspot groups are not assigned the compactness class ‘c’. To avert this possibility, the classification algorithm divides the area of the group by the length of the group. Groups with these ratio values greater than thirty, and that meet all requirements listed above, are assigned the class ‘c’. Groups that are assigned a compactness class of ‘i’ are only required to have greater than three intermediate spots and no mature intermediate spot is required. Finally, any groups not meeting the above criteria are assigned the class of ‘o’, reserved for less developed and smaller bipolar sunspot groups. Figure 10 summarizes this decision process.

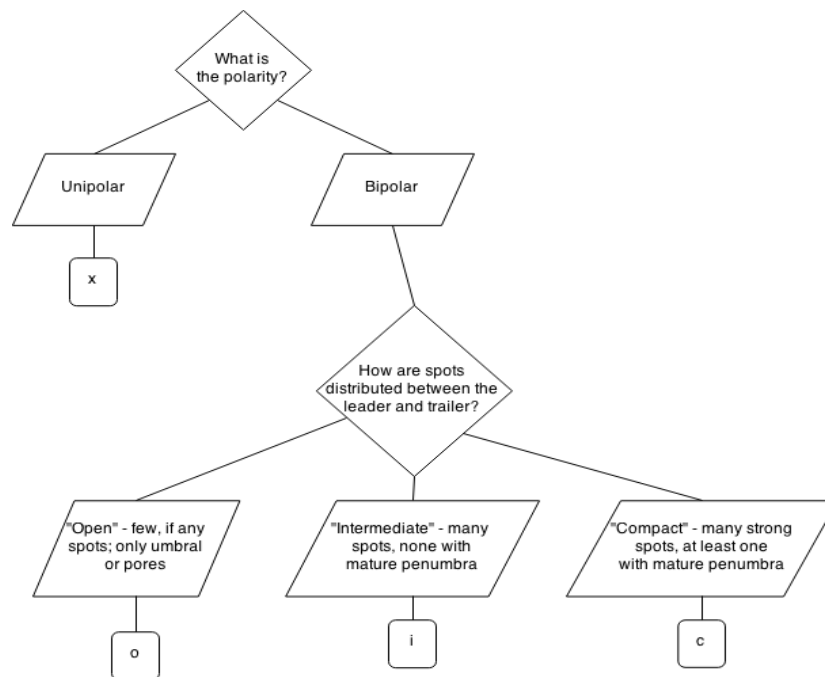


Figure 10. Compactness Classification Decision Tree. Adapted from Howard (2015).

3.4.4 Allowable Classifications

With all the classification rules listed for each of the three tiers of the McIntosh classification system, it is understandable that certain combinations of letters are not physically possible. For instance, a Zurich class for a unipolar group cannot be assigned with a compactness class associated with a bipolar sunspot group. As it turns out, there exist sixty allowable 3-letter classifications (McIntosh, 1990). These are provided in Table 5.

Table 5. Allowable Combinations of McIntosh 3-Letter Classification Codes

Modified Zurich Class	Penumbra Class	Compactness Class	Number of Unique Combinations
A	x	x	1
B	x	o , i	2
C	r , s , a , h , k	o , i	10
D , E , F	r	o , i	6
D , E , F	s , a , h , k	o , i , c	36
H	r , s , a , h , k	x	5
Total number of allowed combinations:			60

3.5 Sunspot Group Tracking

Automated sunspot tracking encompasses identifying a sunspot feature on a solar image and then identifying that same feature on a solar image some time step ahead of the first image. This is not a big task for manual observation since the person analyzing the solar images maintains memory of previous analysis and has an ability to project that memory to the future and anticipate which sunspots correspond to certain past placements. Manual observing entities, such as SWPC, perform tracking by assigning

group numbers to each analyzed sunspot group. This number typically starts at one at the start of a new solar cycle, with each new identified sunspot group assigned the next available number. This system creates a record of the progression of each sunspot group. Performing this task in an automated code is a bit more difficult. The tracking algorithm in this research code must be provided certain information about the past analysis in order to perform this ability. There are two courses of action for providing this past information. Either the user of the code provides inputs about the tracking parameters of the sunspots, or the code must be permitted to analyze more than one image at a time, allowing it to store and carry over information from the previous image. This tracking algorithm performs both of these functions. If the code is asked to analyze a single image, user inputs provide the only means for tracking. However, if multiple images are to be analyzed the code takes user inputs for the first image and then applies automated tracking to the following images, maintaining consistency with the user inputs.

Feature tracking using digital images is a function utilized by many career fields that aim to analyze life cycles of detected elements. Meteorologists in particular have devised several means for tracking cloud features on meteorological satellite, or METSAT, imagery. Two common means of feature tracking with METSAT are cross-correlation and scale space classification (Mukherjee, 2002). Cross-correlation tracking simply translates a feature from where it was to where it is expected to be based upon known motion parameters. It is a fairly straightforward method, but when used for high density features like clouds that can change dramatically over short periods of time, this method is only expected to be successful at small time steps between images (Mukherjee, 2002). Scale space classification practices take a more complicated approach by analyzing the boundaries of feature segments and matching a correspondence across images between high curvature points of the feature. This allows the tracking scheme to detect the same feature despite some changes to its shape and requires little to no known information about motion parameters (Mukherjee, 2002).

When deciding on a tracking implementation for this research, a scale space method was first considered. This method allows for changes in feature shape which is common with sunspots transitioning across the solar disk. However, this level of complexity was ultimately deemed unnecessary. Scale space classification performs its own feature detection and does not need outside inputs for successful implementation, but the research code already performs feature detection. Having two different functions within the same code performing feature detection in much different manners and then having to correlate the two different outputs seemed unnecessary and overly complicated. Since the research code already detects features and their centroid location in degrees latitude and longitude, a translational tracking scheme, similar to cross-correlation, was next considered. This method requires information about the motion of the detected features. It just so happens that the differential rotation of plasma on the solar surface, mentioned in Section 2.1, is consistent and predictable. In fact, equation 3 was developed as a means to predict east-west motion of features on the photosphere of the Sun given the latitude of the detected feature (Howard et al., 1990). Given the predictable motion and known location of sunspot groups, the translational method of feature tracking was picked for implementation in this research code.

The first calculation necessary for the tracking algorithm is to determine the change in time between successive images. Each SDO image was downloaded with a date/time group in its filename. This filename is parsed into individual variables for year, month, day, hour, and minute and then the MATLAB command **etime** reads those variables from the two images and calculates elapsed time. Next, once all groups have been detected and labeled on a single image, the tracking algorithm calculates the solar rotation rate at the latitude of each sunspot group using equation 3. The elapsed time between images is applied to this rotation rate to determine the expected longitudinal displacement of each sunspot group between images. Once features on the next solar image are detected, values for latitude and longitude of detected groups are compared to

the expected longitudinal displacement calculated for the sunspot groups of the previous analysis. An exact match between actual location and projected location is not expected due to the slight uncertainty present in equation 3 and sporadic centroid motion which arises due to the constantly morphing sunspot group shape. Therefore a four degree latitude tolerance and an eight degree longitude tolerance are applied to the comparison, allowing projected locations and actual locations to be identified as the same if the difference between the two are within the tolerance. Sunspot groups meeting this criteria are assigned the same tracking number as the corresponding group from the previous image. Each sunspot group from the current solar image is tested against each of the groups from the previous solar image. Only the closest matching groups will be assigned as the same solar feature if multiple groups fall within the tolerance. Sunspot groups that are not identified as having existed in the previous image/analysis are assigned a new tracking number. It is important to note that picking the value of the tolerance can dramatically alter performance of the tracking algorithm. The tolerance must be large enough to account for the uncertainties in motion while still be small enough to prevent assigning different groups in close proximity the same tracking number. Performance of this tolerance, and the overall tracking algorithm, are discussed further in Section 4.6.

3.6 Mount Wilson Magnetic Classification

3.6.1 Automated Approach

The Mount Wilson magnetic classification scheme is a means of additional characterization for sunspot groups that was not implemented by Spahr (2014) or Howard (2015). For this research, an algorithm has been created to read inputs about each detected sunspot group and then determine the corresponding magnetic classification. See Table 4 for available Mount Wilson classifications. Determination of the magnetic classification relies heavily on the HMIB Magnetogram image. Up to this stage in the progression of the research code, the HMIB image has only been used within the

grouping algorithm, described in Section 3.3.2, to determine whether or not a sunspot group displayed a unipolar or bipolar magnetic structure, a necessary input for McIntosh classification. This new magnetic classification algorithm completes a more in depth analysis of the HMIB image.

The Mount Wilson classification algorithm analyzes a single sunspot group at a time. The first magnetic classification, 'Alpha', is the easiest to determine. This classification is assigned to spot groups that are identified as unipolar, which are the groups that have been given the McIntosh Zurich class of 'A' or 'H'. Each of the remaining Mount Wilson classifications describe spot groups with sunspots of both magnetic poles. In order to describe these more complex groups, the algorithm isolates regions of opposite polarity within a single sunspot group using the HMIB image. Then the center of each white and black polarity region is found in pixel space and converted into heliographic degrees longitude and latitude. The separation between the centers of each polarity region is then calculated and saved for comparisons to come. Figure 11 illustrates this separation between polarity regions of a single sunspot group.

Next each polarity region is analyzed separately. A box of pixels is iteratively built around the center pixel of each polarity region with each step in the iteration increasing the size of the box by a single pixel. The method of box building is depicted in Figure 12. At each step, the number of pixels in the box of the same magnetic polarity are summed and compared against the total number of pixels for the entire polarity region. Once the size of the box reaches a certain percentage of the overall polarity region, the extent of the box is calculated and converted to heliographic degrees. These percentages are used as a threshold for assigning separate magnetic classifications and are discussed further below. This process of box building and measuring is completed twice, once for each polarity region of the sunspot group. The box itself is thought to be a good measure of the distribution of sunspots of each magnetic polarity. The Mount Wilson magnetic classifications are in essence a description of distribution of magnetic polarity regions

within the sunspot group. For instance, if all sunspots of a certain polarity are confined to a small region, the extent of the pixel box will correspondingly remain small. However, if there is wide distribution in the sunspots of that polarity then the pixel box will not reach the threshold percentages until a larger extent has been attained, thereby providing the criteria necessary to distinguish between magnetic classifications. Applying the Mount Wilson classifications to these measurements has not been accomplished previously, so this research will seek to determine those relations empirically. Of note, only the larger box created from the two polarity regions is used for magnetic classification since the larger box will better demonstrate the full complexity of the magnetic structure of the sunspot group. In contrast, analyzing the smaller box alone would inaccurately predict a less complex magnetic structure.

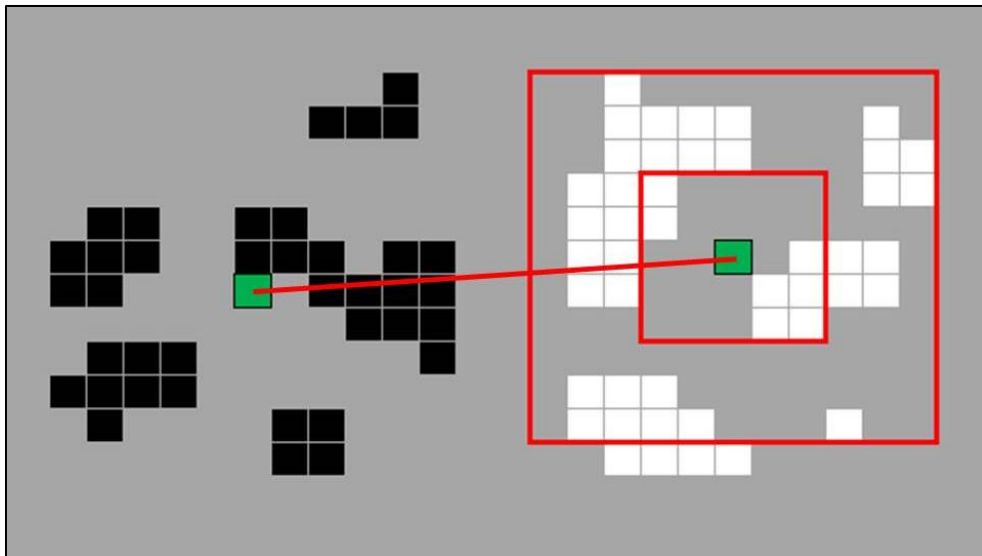


Figure 11. Polarity Region Separation. White and black pixels represent the corresponding magnetic polarity of sunspots in the sunspot group. Green pixels identify the center of each of the two separate polarity regions. The red line demonstrates the separation between the two polarity regions. Red boxes indicate the extent of the polarity box at a low and high percentage of the overall magnetic region.

Next, the extent of the larger box from the previous step is compared against the separation between the centers of each polarity region. This comparison is thought to be a good alternative method of determining whether or not the opposite polarity sunspots are isolated from each other or if they are intermixed within the sunspot group. This distinction is the primary means of distinguishing between the ‘Beta’ and ‘Beta-Gamma’ magnetic classifications. In order to also distinguish the ‘Gamma’ classification, a second threshold percentage is applied in the box building step. In this way, the ‘Beta’ classification will be assigned to groups where the separation between the opposite polarity regions is larger than the extent of the pixel box at the higher percentage. This implies the opposite polarity regions have a greater separation, and an easily identifiable distinction between the two regions is more likely. The ‘Gamma’ classification is assigned to sunspot groups where the separation between polarity centers is less than the extent of the pixel box at the lower percentage. This implies that there is very little to no separation between the two polarity regions and that opposite polarity spots are heavily intermixed. The ‘Beta-Gamma’ classification is assigned when the separation between the polarity regions falls between the higher and lower percentages of the pixel box extent. As a result, this classification is identifying partial separation of polarity regions. Determination of the upper and lower percentages that produces maximum assignment accuracy is discussed in the next section. The separation distance, low percentage extent, and higher percentage extent are demonstrated in Figure 11.

Finally, the conditions for the ‘Delta’ classification must be tested. This piece of the algorithm calls on the umbra map created by the thresholding algorithm described in Section 3.2.4. The umbra map is simply a binary image with each pixel associated with umbrae given a value of one. All other pixels, including those that correspond to penumbra, are assigned a value of zero. This map is used to identify only the umbrae of the given sunspot group being tested, and the resulting image is then multiplied with the HMIB Magnetogram image. The result is an umbra map that contains magnetic polarity

information. Each umbra is then tested to see if multiple umbrae exist within the same penumbral region. If so, these identified umbrae are tested for opposite magnetic polarity. If any sunspots within the sunspot group have multiple umbrae of opposite polarity, the classification of ‘Delta’ is appended to the magnetic classification already assigned.

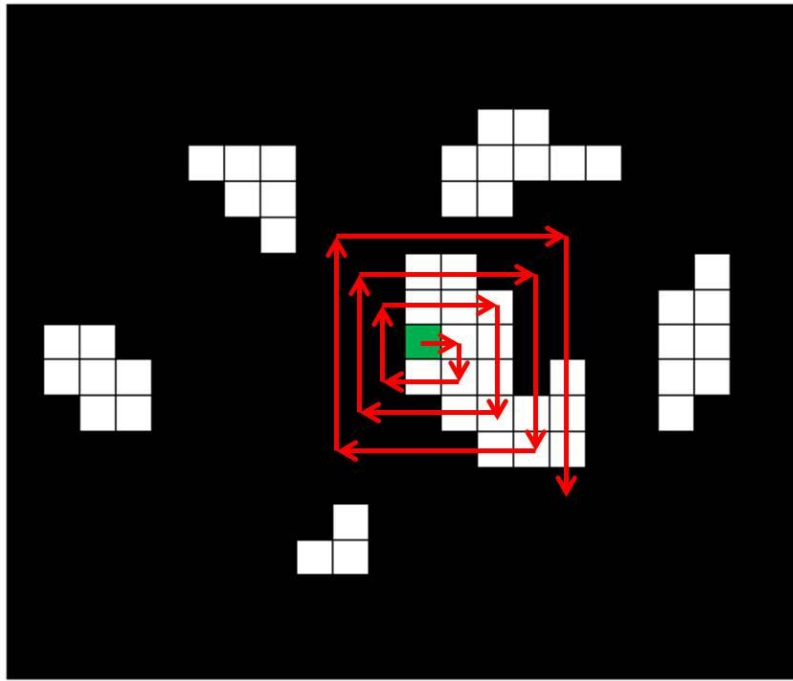


Figure 12. Demonstration of Iterative Box Building. The green pixel represents the center of the polarity region (identified by white pixels). At each step, the size of box is increased by one pixel following the red line so that more and more white pixels are eventually contained by the box. The looping routine is stopped once the number of white pixels enclosed by the box reaches a certain percentage of the overall polarity region.

3.6.2 Development of the Magnetic Algorithm

Development of the Mount Wilson algorithm involved testing the box building technique and threshold percentages described in Section 3.6.1 on 25 days of sunspot data and then comparing the results against SWPC published magnetic classifications.

The 25 days selected comprised a wide assortment of sunspot group complexity, ensuring that algorithm development would have a chance to test each of the unique Mount Wilson classifications. Note that the ‘Gamma’ magnetic classification was not once observed over the course of 3 years of SWPC data available for this research. Since the SWPC bulletins are the primary source of testing, this algorithm was unable to adequately narrow down the conditions for ‘Gamma’ assignment.

Soon after beginning the testing phase, it became apparent that the same threshold percentages could not adequately describe all sunspot groups for magnetic classification assignment. The solution arrived at includes applying separate threshold percentages based upon the size of the sunspot group being analyzed. Remember, in the process of assigning magnetic classifications the extent of the polarity box at each of the two threshold percentages is compared against the separation between polarity regions. Table 6 below describes values arrived at during the 25 day testing period. Unipolar sunspot groups are assigned a designation of ‘Alpha’. Table 6 only describes parameters necessary for magnetic classification for bipolar sunspot groups. ‘Beta’ classifications are assigned if the separation between the two polarity regions is greater than the extent of the pixel box at the higher percentage threshold. ‘Beta-Gamma’ classifications are assigned when the separation between polarity regions falls between the extent of the pixel box at the low and high threshold percentages. Finally, ‘Gamma’ classifications are assigned when the separation between the two polarity regions is shorter than the extent of the pixel box at the low threshold percentage. Again, note that an exact parameter for ‘Gamma’ classification could not be determined without adequate availability of corresponding observations. Consequently, the low threshold percentages of Table 6 were picked such that the ‘Gamma’ assignment would not be impossible but nevertheless very unlikely. Figure 13 provides examples of magnetic classifications and associated magnetogram and intensitygram images.

Table 6. Derived Mount Wilson Classification Parameters for Bipolar Groups. Area refers to the size of the sunspot group in MoSH. Extent of the pixel box at the low and high percentages of the polarity region are compared against the separation between the two polarity regions.

	Low %	High %
Area ≥ 300	10%	95%
$300 > \text{Area} \geq 100$	5%	85%
Area < 100	10%	80%

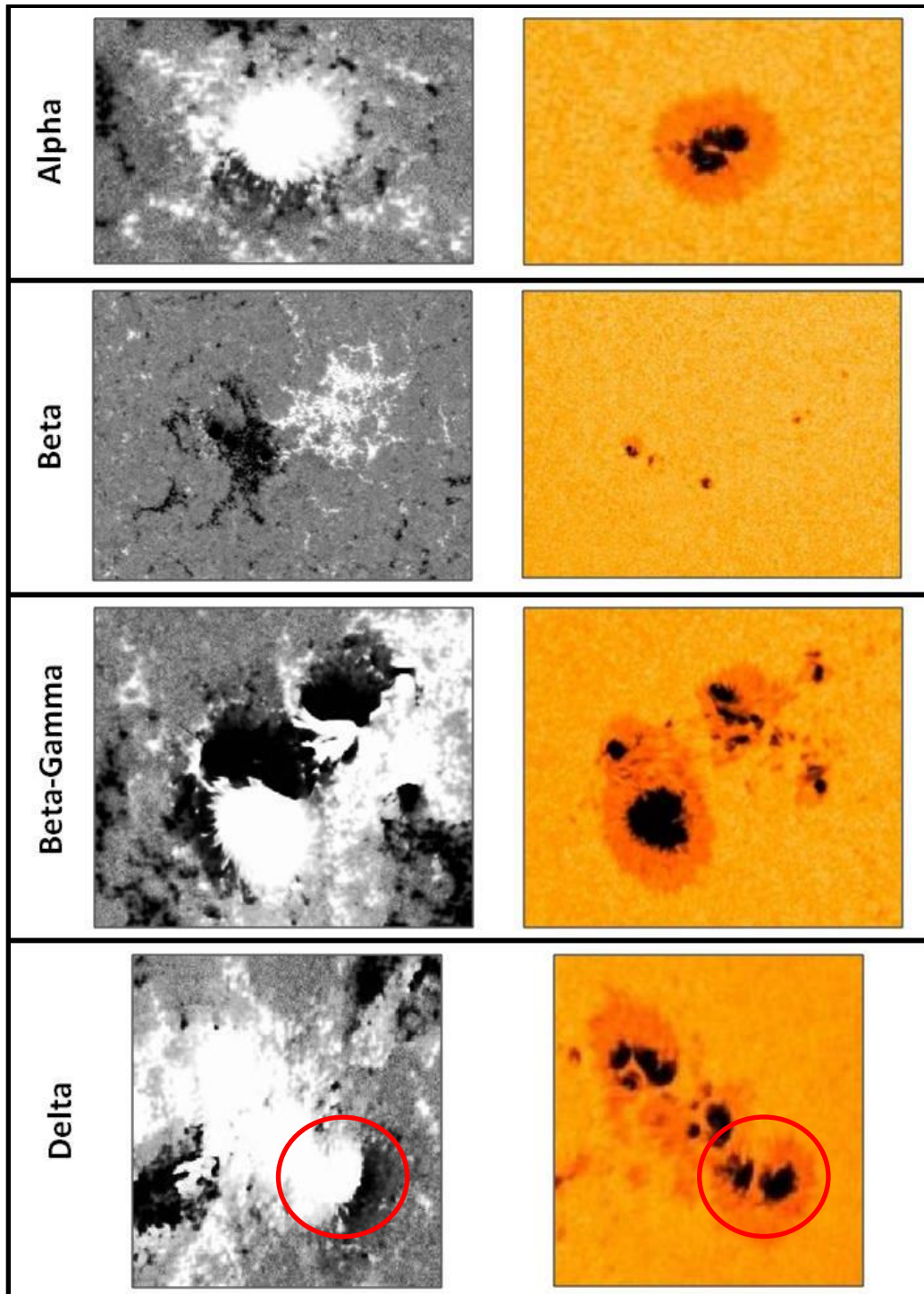


Figure 13. Mount Wilson Classification Examples. Corresponding Magnetogram and Intensitygram images are given side by side. Note the delineation of regions of opposite polarity. 'Gamma' classifications are quite uncommon and are not represented.

IV. Analysis and Results

Chapter III described development and functionality of the research code. Chapter IV now focuses on the output of the research code and how that output stacks up against manual sunspot observations published daily by SWPC. Many of the comparisons to come will mirror those performed by Spahr (2014) in order to develop a longer, consistent record of automated SDO sunspot classification performance. However, unlike Spahr, this research can only compare the automated output of the research code to a single data source due to the termination of archival data from the Holloman AFB solar observatory. This limits the scope of comparisons to come, but all is not lost. SWPC Solar Region Summaries (SRS) take into account the sunspot classifications performed by the Holloman observatory, as well as two other USAF solar observatories. In this way, sunspot information published by SWPC demonstrates a *de facto* average of the three USAF solar observatory data sets. This is fortunate as the intended beneficiary of this research is USAF space weather operations.

4.1 Summary of Code Output

The primary output of this research code is a text document listing the latitude, longitude, length, area, number of umbrae (number of individual sunspots), the McIntosh classification, and finally the tracking number assigned to every detected sunspot group and its magnetic classification. A sample of this text output is given below in Figure 14. Each line of the output details the specifics of a single sunspot group. Each day may contain several lines of data depending on the number of sunspot groups present on the Sun at the time of image being analyzed.

ID	YYYY	MM	DD	HHMM	Lon	Lat	Length	Area	Umbras	McIntosh	Region	Mag_Type
SDO	2014	10	23	2000	1.77	-13.06	26.28	3463.05	347	Fkc	1	Beta-Gamma-Delta
SDO	2014	10	23	2000	-35.59	-11.92	5.31	60.20	7	Dao	2	Beta
SDO	2014	10	23	2000	44.25	5.28	5.43	62.57	10	Dro	3	Beta
SDO	2014	10	23	2000	-59.97	7.63	7.67	37.13	4	Dao	4	Beta
SDO	2014	10	23	2000	-69.76	9.22	0.78	6.53	1	Axx	5	Alpha
SDO	2014	10	23	2000	55.96	-10.59	0.31	1.72	1	Axx	6	Alpha

Figure 14. Sample Output from the Automated SDO Research Code

Code output has been generated for the span 1 July 2013 through 31 July 2015. Each day over that span is represented by a single SDO image in order to perform proper comparison with SWPC classifications that are made available once every 24 hours. One of the benefits of this code, however, is that analysis of solar images can be conducted as frequently as is desired by the user, only being limited by the frequency of available solar imagery.

It is important to note that SWPC SRS bulletins are valid each day at 0030Z, but the sunspot classifications incorporated into the SRS bulletin are performed 4-8 hours before that time depending on the availability of uninterrupted viewing of the Sun from the three USAF ground-based solar observatories (AFWAMAN15-1). As a result, the time for which SWPC bulletins are based changes day to day, and matching exact times with the SDO images to be analyzed and compared is impossible. With that in mind, a SDO image valid time of 2000Z is picked for every day over the two year period. Consequently, daily comparisons of automated SDO classifications to manual SWPC classifications may be based upon views of the Sun from slightly different times of day.

Occasional interruptions in the SDO data feed means that certain images are unavailable for download from the SDO archive. These data interruptions are fairly infrequent but nevertheless resulted in 52 days of SDO data made unavailable over the 25 month analysis period. Rather than try to find the next closest valid SDO image of a missing image and add additional inconsistencies into the comparisons, those 52 days

have been completely removed from the analysis process. The corresponding 52 days of SWPC SRS bulletins were removed to ensure proper one-to-one comparison.

4.2 Comparison Objectives

Comparisons detailed below have two main objectives. The first is to compare the automated classifications produced from the research code to the manual observations made available by SWPC. This is done because manual observing provides a baseline for analysis, ensuring the automated data is not way off the mark. Remember that this research code was not developed specifically to match manual observations, and differences highlighted by the comparison process are expected. The second objective is to see how these comparisons match those conducted by Spahr (2014). The detection and classification algorithms of the research code in general have not been altered, except when explicitly identified, from that used by Spahr. This was done to ensure that any differences in our research data, if discovered, can be attributed to reasons other than inconsistent coding.

4.3 Area, Group, and Spot Accuracy

The first three parameters to be compared between the automated SDO analysis and the SWPC sunspot data source are area of each sunspot group in MoSH, number of groups detected, and number of individual spots detected. Note that the data points described below are daily totals. As such, a single sunspot or sunspot group that exists on multiple, consecutive SDO images will contribute to more than one data point, being counted toward the totals again and again so long as that sunspot or group is still visible.

4.3.1 Area

Sunspot group area is measured in MoSH and calculated for each day of the 25 month period for both data sources. The area calculated for each day is simply the total sum of areas from individual spot groups. Figure 15 demonstrates the direct comparison

between SWPC data and the automated SDO data from this research code. A best linear fit line, or regression line, is applied to the comparison data, and one standard deviation from the fit line is identified on the plot.

The equation for the best fit line, as shown in Figure 15, reveals a slope of 0.97. This implies that corresponding data points from the two data sources see near identical rise and fall in summed area day to day. Generally speaking, this is a good result for direct comparisons. However, the y-intercept value of 104.21 suggests that SWPC daily area calculations are still on average 104.21 MoSH larger than the corresponding SDO automated calculation. This offset is likely due to a difference in area calculation schemes between the data sources. This research code calculates area by summing up pixels identified as sunspots in a sunspot group and then converting that pixel area into MoSH. In this way, only umbra and penumbra area is calculated. Manual observing procedures at the Holloman solar observatory are outlined by Spahr (2014) and Howard (2015). These procedures dictate that group area be calculated by fitting an ellipse to the sunspot group and then using the known area of the ellipse as the group area. This process is ideal for lower resolution imagery where analysts have limited ability to depict small details. However, this process invariably adds some of the surrounding solar surface into the area calculation. This difference in procedures seems to be the primary cause of the area offset described above. Note that it is unknown at the time of this research whether SWPC applies any additional procedures in the calculation of group area. The *R squared* parameter from regression analysis conveys how well a linear fit line describes the variance in data points. Generally speaking for this research, a higher value of *R squared* demonstrates a higher confidence in the linear fit line. The *R squared* value of 0.83204 for this comparison suggests relatively high confidence in the analysis above.

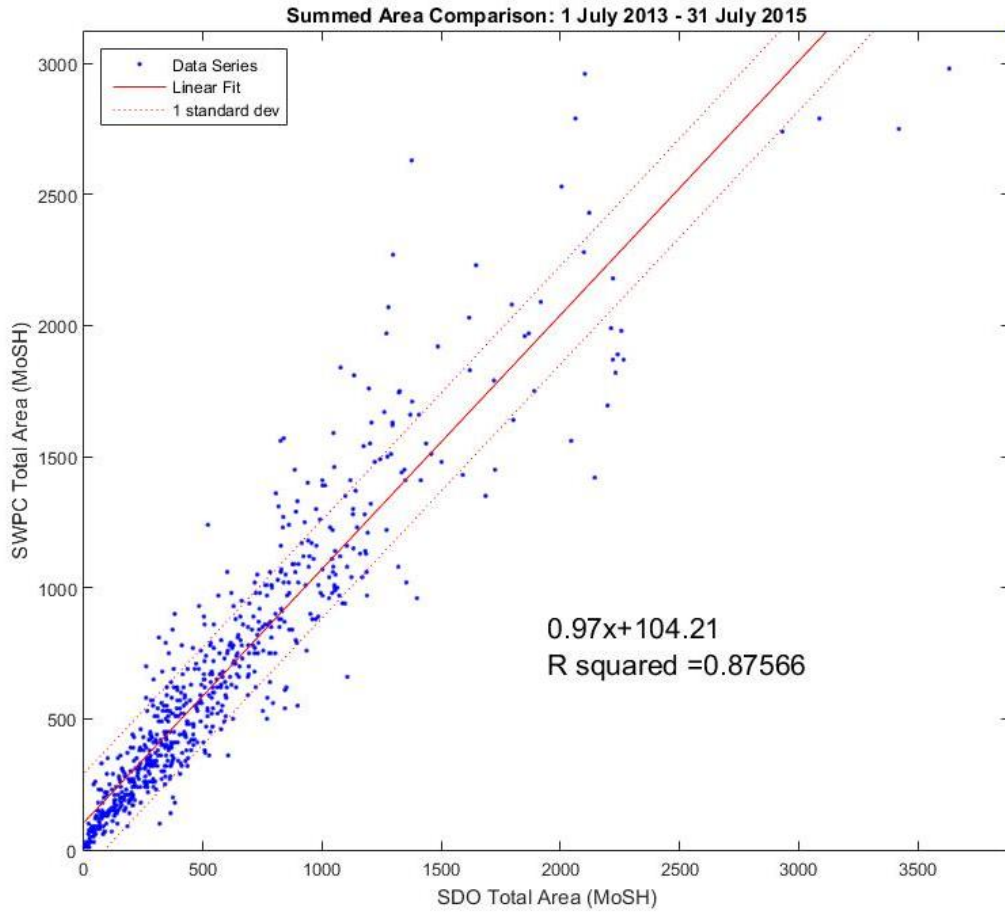


Figure 15. Area Comparison between SDO and SWPC Data Sets. Each blue data point represents a single day of comparison. The best fit line is defined by $y = 0.97x + 104.21$. The R squared value is 0.87566.

4.3.2 Number of Groups

The number of sunspot groups per day is summed for both data sets and compared much like in Section 4.3.1. The linear regression line and statistical parameters are provided in Figure 16. Many of the data points in Figure 16 overlap one another resulting in the reduced number of apparent data points. Instead of a single data point for each of the 761 days of the analysis period, there are only 94 unique positions on the plot above. This is due to the limited number of observed groups per day. We rarely see more than 10 individual sunspot groups on the solar disk at a single instance. The slope of the best fit

line for this comparison is 0.61, suggesting that the automated SDO code identifies many more sunspot groups than manual observers. This is an expected outcome due to the high spatial resolution of SDO imagery and the thresholding technique used to identify sunspots. This research code is able to identify single pixels falling below the threshold value that a manual observer is incapable of seeing. For reference, over the 25 month analysis period, the research code detected 5077 sunspot groups while SWPC reported 4179. Of the extra SDO spot groups, 77% are classified as ‘Axx’, the McIntosh classification assigned to the smallest unipolar groups. These are the groups that are often only one or two pixels in size on the SDO Intensitygram and are far too small to be seen by the naked eye on lower resolution imagery. The method for identifying these extra sunspot groups is discussed in Section 4.4. The y-intercept in this case is 0.94 which slightly reduces the difference in number of spot groups between the two data sets each day, thereby slightly reducing the apparent poor quality in the comparison as seen in the slope of the linear regression line. However, the *R squared* value of 0.57243 suggests only modest confidence in the above linear fit line. This low value is exacerbated by only having 94 unique plot points, allowing outlier points to have a greater negative effect on the regression analysis. The frequent detection of very small sunspot groups by the research code explains the outliers below the regression line in Figure 16. The outliers above the regression line, depicting days when SWPC detected more groups than the SDO code, are further discussed in Section 4.4.

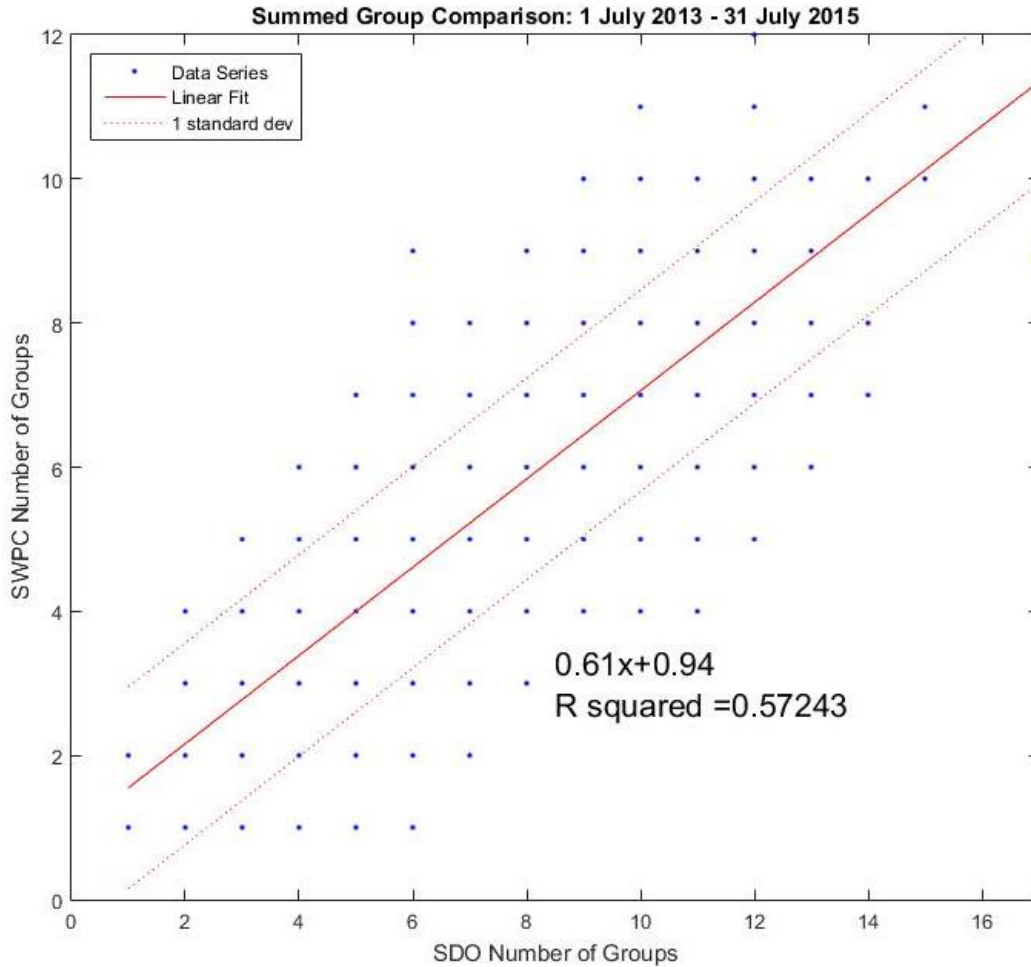


Figure 16. Group Number Comparison between SDO and SWPC Data Sets. Each blue data point represents a single day of comparison. The best fit line is defined by $y = 0.61x + 0.94$. The R squared value is 0.57243.

4.3.3 Number of Sunspots

Next, the total number of individual sunspots is summed for each day of the two data sets. Sunspot groups often contain many individual spots, with more complex groups generally containing the most umbrae (Foukal, 2008). As such, there are many more possible data points for this comparison than in the previous section. Figure 17 displays the regression analysis.

The slope for the regression line in this case is 0.45, suggesting that the research code on average detected around twice as many individual spots as those identified by

SWPC. Again, this is an expected outcome due to the ability of the research code to detect very small sunspots. Additionally, it makes sense that this slope is even less than that for the group comparison from Section 4.3.2 due to the fact that many of the extra umbrae detected are lumped together into spot groups also identified by SWPC. In essence, both data sources could detect the same sunspot group, but the SDO code would identify more individual spots within that group. Small sunspot groups not detected by SWPC only account for a portion of the difference in sunspots detected. Further analysis of this gap between data sources is partially reduced to speculation due to the fact that this research code does not record information for individual umbra the same way it does for sunspot groups. There is no way to identify the specific sunspots that are not detected by SWPC unless those spots are part of a group not detected by SWPC, usually the ‘Axx’ groups. For reference, the SDO automated code detected a total of 52,408 sunspots over the analysis period (SWPC detected 31,816) and only 2,734 (5.2%) of those belonged to the sunspot groups not detected by SWPC. This implies 34.1% of the SDO sunspot total are sunspots only detected by the SDO code that exist within sunspot groups identified by both sources.

There are two probable ways in which the SDO code identifies more umbrae within groups detected in both data sets. The first, as has already been stated above, is the prevalence of the research code to detect small sunspots that may only occupy the size of a couple of pixels on a high resolution image. These occurrences are not limited to regions on the solar disk outside of SWPC detected sunspot groups. The other possible source of additional sunspots may arise from the ability of the code to detect boundaries between very close, but still individual, spots. Manual observations would not necessarily be able to distinguish very narrow or small breaks between separate umbrae and therefore would count a single sunspot, but a pixel by pixel analysis by this research code might detect more.

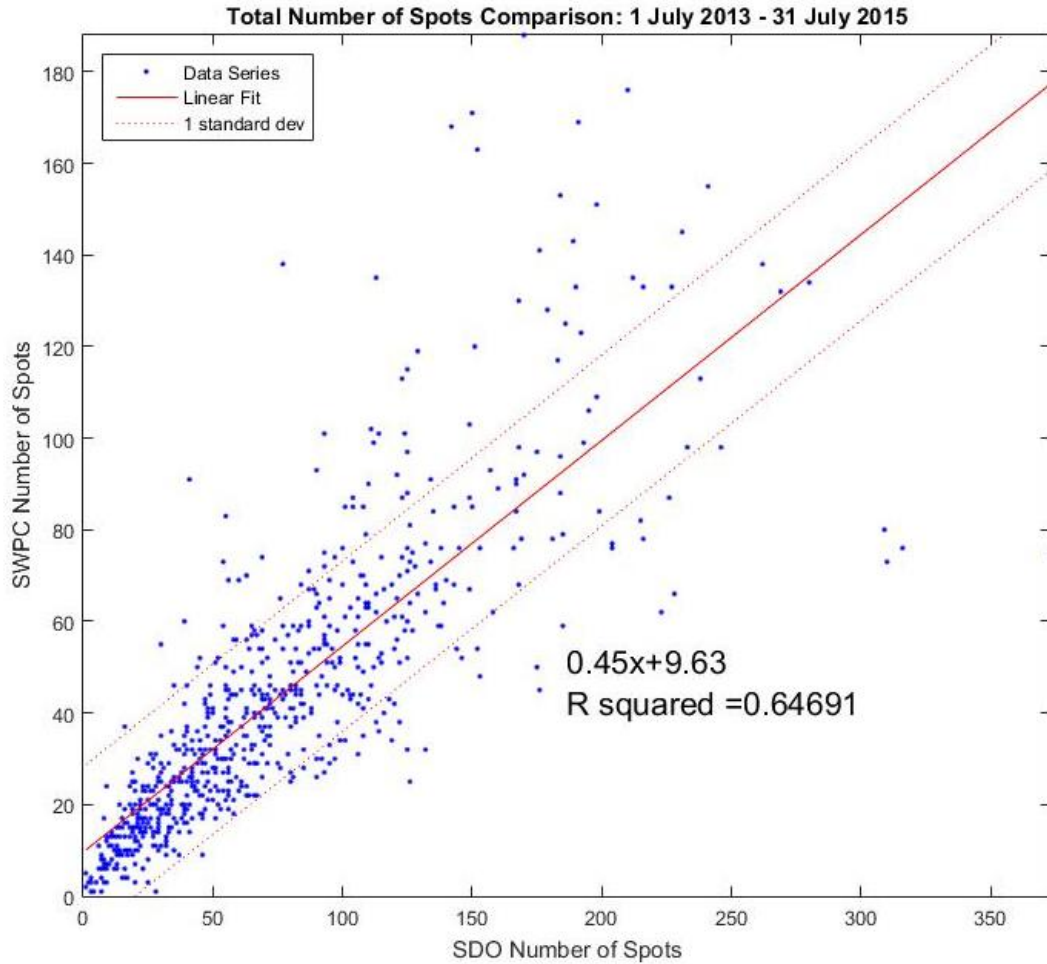


Figure 17. Sunspot Number Comparison between SDO and SWPC Data Sets. Each blue data point represents a single day of comparison. The best fit line is defined by $y = 0.45x + 9.63$. The R squared value is 0.64691.

When compared against the extent of the plot in Figure 17, the y-intercept of 9.63 is a fairly small correction. However, toward the lower left portion of the plot, an adjustment of 9.63 is nevertheless meaningful. These data points represent days when the Sun was fairly inactive with less complex sunspot groups and, as a result, fewer individual sunspots were identified. Consequently, a regression line only applied to this lower left portion of the plot would have a slope value much closer to one, implying similar detection ability between the automated code and manual observation. Higher to the right in the plot, data points are indicative of a more active solar surface dominated by

complex sunspot groups. There is much less agreement between the two detection schemes in this portion of the plot, and this disagreement is evidenced by the *R squared* value of 0.64691 which again indicates only a moderate confidence in the linear fit line's ability to represent the data. Viewing these two details together suggests that manual observing and the automated SDO code perform similarly on days with an inactive Sun, but more disagreement arises during active Sun periods. In essence, this is an indicator that the research code is performing appropriately as one would expect the opportunity to detect very small spots, the expected primary cause of sunspot number deviation, to increase when the Sun is active. Conversely, a large consistent disagreement between the two data sources across all data points would suggest the research code was flawed even though the *R squared* value might increase in such a case.

4.3.4 Comparison with Spahr Results

Spahr (2014) also performed linear regression analysis for area, number of groups, and number of sunspots over the time period July 2012 through June 2013, broken into two 6-month segments. Regression analysis performed by Spahr (2014) for the period of January 2013 through June 2013 seems to follow a consistent method and is therefore compared against the results from this research. Table 7 summarizes the results found by Spahr (2014) for this period of time, and includes the corresponding regression analysis from this research for comparison.

Table 7. Comparison of Linear Regression Analysis. Regression analysis for area, number of groups, and number of sunspots between the SWPC data set and automated SDO output performed by Spahr (2014) for the period of Jan 2013 – Jun 2013 is identified in the first block of rows. Regression analysis from this research is given for the corresponding monthly segments.

		Slope	Y-Intercept	R Squared
Jan 2013 – Jun 2013	Summed Area	1.04	85.27	0.812
	Number of Groups	0.67	0.56	0.583
	Number of Sunspots	0.45	6.40	0.747
Jan 2014 – Jun 2014	Summed Area	0.97	125.86	0.825
	Number of Groups	0.55	1.89	0.569
	Number of Sunspots	0.55	8.26	0.704
Jan 2015 – Jun 2015	Summed Area	1.00	70.59	0.842
	Number of Groups	0.55	0.86	0.542
	Number of Sunspots	0.45	5.90	0.713

4.4 Method of Classification Comparison

The next comparison conducted between the SWPC data set and the automated SDO research code output analyzes the assigned McIntosh classifications. As will be shown in Section 4.5, identical classifications between the two sources for the same sunspot group are uncommon. This is due to various reasons including ambiguity in the classification descriptions, small adjustments arising from application of those descriptions to an automated code, and differences in how sunspots are assigned to a group between the two sources. Additionally, the large number of unique 3-letter McIntosh codes provides ample opportunity for the two classification schemes to diverge. Note that the differences in classification between the two sources are not an indicator of

poor performance by either entity, so long as both sources apply a valid and justifiable McIntosh classification scheme. Manual observation is the ‘tried and true’ classification method. Analysis of the comparisons to come provides the justification for the validity of the automated SDO research code.

The first step in the McIntosh classification comparison is to match sunspot groups. Up to this point only daily totals have been evaluated. Now, each sunspot group from the SDO automated analysis must be matched to its corresponding spot group from the SWPC data set for each day of the analysis period. Spahr (2014) created a matching algorithm that compares latitude and longitude of group centroids day to day between the two sources, applying a tolerance of 10 heliographic degrees for matching purposes. If multiple groups fall within the 10 degree tolerance, the groups that most closely match are assigned to be the same group. The reader is directed to Section 4.3 of Spahr’s thesis for the decision process and a more in-depth description of the matching algorithm. As one would expect, this matching process is not perfect. Some groups that should not be matched will be put together, and other groups that are the same feature will not be matched. This is known limitation, but is ultimately accepted with the understanding that these errors will slightly skew the comparison results. Any groups that are not matched are subsequently removed from the comparison process. Typically, unmatched groups from the SDO data set are of the ‘Axx’ McIntosh class, representing sunspot groups not identified by manual observers. Far fewer unmatched groups come from the SWPC data set, and it is thought that these largely arise due to differences in grouping procedures. For example, the SDO research code may identify a single sunspot group where the SWPC bulletins identify two or more unique sunspot groups. This possibility comes from slight differences in interpretation of the McIntosh grouping rules discussed in Section 3.3. As a result, both data sources may record the same solar feature in two different ways, creating an apparent disagreement in the matching process. Occasionally, groups identified by SWPC at or very near the extreme limbs of the Sun are not identified by the

SDO research code as well. The extent of the solar surface is slightly reduced in the limb darkening correction phase of the code, limiting the ability of the research code to detect sunspot groups near the solar limbs. Consequently, these SWPC groups are also left unmatched.

In order to accurately compare the matched sunspot groups, a consistent and logical application of the McIntosh classification codes needs to be applied. The first step is to understand the typical life cycle of a sunspot group. Spot groups most often originate as a single, unipolar group (Foukal, 2008). As time passes, these groups may become larger and more complex (bipolar) corresponding to an increase in magnetic flux through the solar surface. As the expanse of the spot group increases over time, eventually the magnetic flux in that region will begin to decrease and the sunspot group will start to decay. The remnants of the sunspot group will return to a unipolar configuration before fully disappearing. Spahr (2014) aligned the sixty McIntosh classification codes to mirror this cycle. Table 8 demonstrates this alignment. Ideally, newly developed sunspot groups will start at the first code in Table 8 and progress upwards in number toward more complex configurations and then return in the same manner as the sunspot group decays.

Table 8. McIntosh Classification Alignment to Expected Spot Group Lifecycle. Adapted from Spahr (2014).

Col/Row	Class	Col/Row	Class	Col/Row	Class	Col/Row	Class
1	Axx	16	Chi	31	Dki	46	Ekc
2	Hrx	17	Cko	32	Dkc	47	Fro
3	Hsx	18	Cki	33	Ero	48	Fri
4	Hax	19	Dro	34	Eri	49	Fso
5	Hhx	20	Dri	35	Eso	50	Fsi
6	Hkx	21	Dso	36	Esi	51	Fsc
7	Bxo	22	Dsi	37	Esc	52	Fao
8	Bxi	23	Dsc	38	Eao	53	Fai
9	Cro	24	Dao	39	Eai	54	Fac
10	Cri	25	Dai	40	Eac	55	Fho
11	Cso	26	Dac	41	Eho	56	Fhi
12	Csi	27	Dho	42	Ehi	57	Fhc
13	Cao	28	Dhi	43	Ehc	58	Fko
14	Cai	29	Dhc	44	Eko	59	Fki
15	Cho	30	Dko	45	Eki	60	Fkc

A three-tiered approach is applied when comparing the McIntosh classifications of the SWPC and SDO research code data sets. The first tier describes the direct comparison between the 3-letter classifications of the two data sets. If both of the matched groups have the exact same McIntosh classification, this tier is met in the comparison process. The ‘intermediate’ tier describes matched sunspot groups that have the same Zurich coding, or first letter of the 3-letter McIntosh classification. For example,

a matched pair with a classification of ‘Cao’ from the SWPC data set and a classification of ‘Cki’ from the SDO research data set would meet the requirements for this tier of comparison. The final, or ‘relaxed’, tier in the comparison process takes note of when matched groups have McIntosh classifications that are no more than one Zurich code removed from the other following the structure of Table 8. For example, a classification of ‘Cao’ from the SWPC data set paired with a spot group classified as ‘Dhi’ from the SDO research data set would meet this tier of comparison. This third tier of the comparison process relies heavily on the alignment of the McIntosh codes described above since any paired groups meeting this comparison tier are understood to be in a similar stage of development. Without the physical meaning present in Table 8, this tier of comparison would not provide insight into the performance of the SDO automated classification code. Figure 18 provides a visual depiction of this three-tiered approach to comparing matched sunspot groups. Columns and rows are labeled 1-60 and represent the corresponding McIntosh classifications in Table 8. All matched groups between the two data sets are compared in this manner and the number of ‘direct’, ‘intermediate’, and ‘relaxed’ hits are recorded as a percentage of the total number of matched sunspot groups. Comparison percentages are provided in Section 4.5.

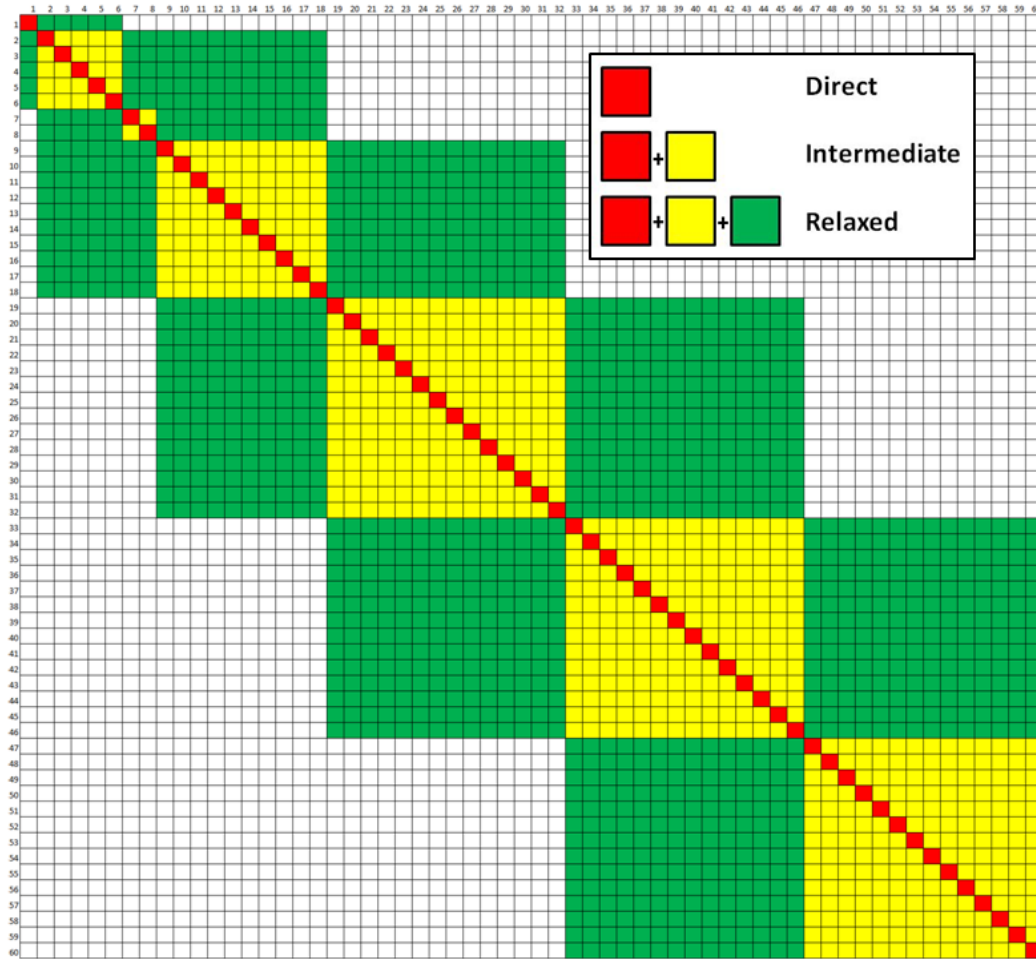


Figure 18. Three-tiered Comparison of McIntosh Classifications. Rows/columns represent the corresponding McIntosh Classification of each data set. The gridded location of each matched sunspot group pair determines if one of the three tiers of comparison is met. Adapted from Spahr (2014).

4.5 Classification Accuracy

Classification comparisons have been conducted for the period of 1 July 2013 – 31 July 2015. Results are provided in Table 9 and are displayed alongside the comparison results of Spahr (2014) spanning the period July 2012 – Jun 2013. A cursory examination of the values suggests that the research code has remained fairly consistent over three years of analysis. Spahr (2014) also compared a SWPC data set to raw classification data from the Holloman AFB solar observatory for the same period of July 2012 – Jun 2013.

As means of providing some context for the results in Table 9, Spahr found a ‘direct’ metric value of 33.55%, an ‘intermediate’ metric value of 58.38%, and a ‘relaxed’ metric value of 87.45% for this alternative comparison. These values reveal improved agreement in classification assignment between the two manual observing entities, but do, nevertheless, show a similar trend to the data below. Perfect agreement in McIntosh classifications between any of the observing entities is not possible and is not the objective of this research.

Table 9. Three-tiered Comparison Results. Summary of results for the three-tiered comparison of McIntosh classifications between the SWPC and SDO research code data sets. The first two columns represent the results of Spahr (2014).

	July 2012 - Dec 2012	Jan 2013 - Jun 2013	July 2013 - Dec 2013	Jan 2014 - Jun 2014	July 2014 - Dec 2014	Jan 2015 - July 2015	3 year average
Direct	13.46%	20.22%	15.25%	18.12%	20.64%	18.32%	17.67%
Intermediate	49.26%	51.25%	46.19%	51.77%	50.53%	49.53%	49.76%
Relaxed	83.74%	83.80%	78.72%	82.81%	83.75%	80.16%	82.16%

A more thorough analysis of the distribution of the metric values taken at a monthly interval reveals that the largest standard deviation in data points is observed for the ‘intermediate’ metric (5.85%). The ‘direct’ metric sees the next highest standard deviation (5.18%) while the ‘relaxed’ metric sees the lowest standard deviation (3.7%) month to month. Remember that matched sunspot groups falling into the ‘relaxed’ category were assigned McIntosh classifications no more than one Zurich classification removed from the other according to Table 8, demonstrating that both sunspot groups were assigned McIntosh classifications representing a similar stage of sunspot group development.

An assumption going into this research was that the automated SDO code would perform better, when compared against SWPC, for sunspot groups located nearer the center of the solar disk as opposed to groups near the limbs of the Sun. The idea is that the Wilson effect, as described in Section 2.2, and foreshortening distort the appearance of the sunspot group while it is located near the limb of the Sun. These effects occurs in addition to normal growth or decay processes that morph sunspot group shape. The SDO Intensitygram images can only be interpreted explicitly based upon the actual appearance of the sunspots. As a result, both factors act to change the McIntosh classifications assigned by the SDO research code. On the other hand, a manual observer, or even a machine-learning automated classification scheme, could account for the changes resulting from the Wilson effect and foreshortening by projecting what the sunspot group is expected to look like despite its appearance at the solar limbs. Consequently, these methods would assign a McIntosh classification that potentially better matches the actual growth and decay of the sunspot group over time. In this way the true time evolution of the sunspot group could be better tracked by the manual observer as opposed to this research code. To test for whether or not this effect revealed itself in the analysis of SDO images between 1 July 2013 and 31 July 2015, the three-tiered comparisons described above were completed again using various cutoff longitudes. The thought is that only comparing sunspot groups closer to the center of the solar disk will improve each of the comparison metrics between the two data sources due to the reduced impact from the Wilson effect. Table 10 provides the results of the additional testing.

Table 10. Three-tiered Comparisons Utilizing Longitude Cutoffs. Comparison metrics were recalculated utilizing longitude cutoffs of sunspot data for the full analysis period, 1 Jul 2013 – 31 Jul 2015. Values in parentheses demonstrate the percent difference from the corresponding ‘No cutoff’ metric value.

	No cutoff	70° cutoff	60° cutoff	50° cutoff	40° cutoff
Direct	17.19%	18.26% (6.22%)	18.42% (7.16%)	18.77% (9.19%)	19.86% (15.53%)
Intermediate	49.10%	49.82% (1.47%)	49.24% (0.28%)	48.38% (-1.47%)	48.55% (-1.12%)
Relaxed	80.65%	81.44% (0.98%)	81.31% (0.82%)	80.45% (-0.25%)	80.65% (0.0%)

The results in Table 10 demonstrate an evident improvement in the ‘Direct’ metric while the ‘Intermediate’ and ‘Relaxed’ metrics saw little to no improvement from applying a longitude cutoff for sunspot group comparisons. This implies that the second and third letters of the 3-letter McIntosh classification system are the primary variables altered by narrowing the scope of the sunspot group analysis. The ‘Intermediate’ and ‘Relaxed’ metrics look at the Zurich class of the McIntosh classification alone. The penumbra and compactness classes are only a factor in the ‘Direct’ comparison. This conclusion actually makes sense if the improvements seen in the ‘Direct’ metric are to be attributed to the Wilson effect. The penumbra and compactness classes of the McIntosh classification system deal with the shape, symmetry, and distribution of intermediate sunspots. Shape and symmetry should understandably change as the Wilson effect causes sunspots to change appearance over time. Additionally, many smaller sunspots between the larger leading and trailing spots could be expected to disappear entirely from view due to the Wilson effect, thereby altering the sunspot group compactness classification. Overall length of the sunspot group, as categorized by the Zurich class, should not see as much change from the Wilson effect. Group length is calculated between the leading and trailing sunspots, typically spots that are larger and more mature. These sunspots would

indeed change in appearance due to the Wilson effect but are less likely to disappear altogether. The result is little to no change in the sunspot group length calculation and correspondingly little change to the sunspot group Zurich classification. Ultimately, the improvement for the ‘Direct’ metric seen in Table 10 still represents a small percentage of the overall deviation between the two data sources, but being able to attribute this error to the Wilson effect nevertheless improves overall understanding of the performance of the automated SDO code.

4.6 Tracking Accuracy

Testing of the feature tracking algorithm described in Section 3.5 was conducted over the period of 1 Jun 2015 through 31 Jul 2015. Various time intervals between consecutive images were tested, and results are summarized in Table 11. In order to determine whether or not a sunspot group was properly tracked between images, the tracking number of each group was listed on each of the solar images for visual inspection of the tracking accuracy. Correct matches imply that the same sunspot group was correctly given the same tracking number on both images. An incorrect match implies that either different features were assigned the same tracking number or the same feature was assigned different tracking numbers. Sunspot groups were not counted as correct or incorrect matches if they only appeared on a single image. This third outcome was commonly witnessed for ‘Axx’ sunspot groups that never developed into mature sunspot groups and consequently had very short lifecycles. Sunspot groups passing across the western limb of the Sun and out of view also fell into this third category.

Table 11. Testing Results for Tracking Algorithm. Numbers of correctly and incorrectly tracked sunspot groups are listed at each interval between consecutive images. Sunspot groups that are not counted only appeared on a single image and therefore could not be tracked.

	12 hour interval	24 hour interval	48 hour interval	96 hour interval
Correct	435	217	92	31
Incorrect	0	0	0	1
Not Counted	201	121	67	52
Total Groups	636	338	159	84

The results above utilized a longitude tolerance of eight heliographic degrees and a latitude tolerance of four heliographic degrees for matching assignment. Additionally, the longitude tolerance was automatically increased beyond the eight degrees for particularly long time intervals in order to account for increasing uncertainty in position at those time scales. The first error in the feature tracking testing did not occur until the interval between images increased to four days. This result provides a very high confidence in tracking ability and tracking number assignment on shorter timescales. In fact the single error encountered at the 96-hour interval was the result of greater north-south movement of the feature than the latitude tolerance. This can be corrected by adjusting the latitude tolerance to automatically increase at longer time scales much like the longitude tolerance. Note that the primary reason for developing the feature tracking algorithm was to develop databases demonstrating how a single sunspot group evolves over time. At larger timescales between images, many of the details of the sunspot group evolution are lost due to low time resolution, negating the intended purpose of the algorithm.

4.7 Mount Wilson Classification Accuracy

4.7.1 Initial Testing

With the Mount Wilson classification algorithm from Section 3.6 in place, it is now time to conduct testing on its performance. Note again that the magnetic classifications assigned by the automated code are being tested against corresponding SWPC data sets. As was discussed with the McIntosh classification comparisons, SWPC classifications should be considered as a reliable interpretation of the available rules governing these classifications. The Mount Wilson algorithm was built with the intention of closely matching SWPC magnetic classifications.

Two months of SDO images were analyzed at first with the updated Mount Wilson classification algorithm to give some measure initial performance. It is understood that full confidence in this algorithm will only come after additional testing, and the analysis below should be considered as based upon preliminary results. November 2013 and May 2014 were selected as good testing periods for their large variety of simple and complex sunspot groups. In order to compare classifications between the data sources, the same sunspot matching scheme was used as that described in Section 4.4. Recall that this matching scheme did not perform perfectly. For reference, 289 sunspot groups were matched for the two month period and nine of those were considered to be incorrect matches due to limitations in the matching algorithm. These sunspot groups were therefore removed from the analysis and are not represented in the data below. The remaining matched groups were compared directly between the two data sources.

The first magnetic comparison metric compares the number of matched sunspot groups given the exact same magnetic classification between the two data sets to the total number of matched groups. Simply dividing the number of exact classification matches to total number of comparisons produced an accuracy of 56.8% (159 correct out of 280

total). However, this number still includes some correctable errors that skew the results. Certain matched groups between the two sources represent vastly different interpretations of the same sunspot group. This is due to the differing means of grouping together individual sunspots between the automated code grouping scheme described in Section 3.3 and that conducted by manual observers. This same error drove differences in the McIntosh classification comparisons as well. The most notable effect of the differing grouping schemes for the magnetic comparisons were occasions where a unipolar sunspot group from one source is matched with a bipolar group from the other source, creating an immediate discrepancy in the comparison of the magnetic classifications since unipolar groups can only be given a magnetic classification of ‘Alpha’. Both sources are describing the same solar feature, just in separate ways, and the matching scheme does its best to fit two reasonably close sunspot groups together. Analysis of the list of matched sunspot groups revealed that this error occurred 51 times out of the 280 matched groups. Ultimately the Mount Wilson classification algorithm cannot account for these discrepancies in sunspot grouping. Only analyzing the remaining 229 matched groups revealed that the first comparison metric improved to 69.5%. This metric now represents occasions where the automated Mount Wilson algorithm could reasonably be expected to assign the same magnetic classification as the SWPC data source since both sources would be analyzing a similar representation of the same solar feature. This accuracy rating suggests that the Mount Wilson algorithm is utilizing a classification scheme that is indeed able to distinguish necessary differences on the magnetogram images in order to assign the correct Mount Wilson magnetic classification. However, with only seven unique classifications available, it would be reasonable to expect that a reliable magnetic classification algorithm would perform better even after accounting for differences arising out of ambiguity in the descriptions of the different magnetic classes. After careful consideration, it is expected that this Mount Wilson classification algorithm can

be improved, but it will require tweaks to the parameters used to distinguish between separate magnetic classifications.

A secondary magnetic comparison metric takes a more relaxed look at the assigned magnetic classifications. The primary difference in the descriptions of the ‘Beta’ class from the ‘Beta-Gamma’ class is the presence of a clear dividing line between areas of opposite polarity. However, it became clear after examining magnetogram data that such a line is only occasionally evident, even when corresponding SWPC data is reporting the ‘Beta’ classification. In practice, the ‘dividing line’ descriptor is a difficult parameter to measure, especially with an automated classification code. The result is a blurred difference between the ‘Beta’ and ‘Beta-Gamma’ classes. This secondary metric removes this disparity. Occurrences where one source assigns the ‘Beta’ classification and the other source assigns the ‘Beta-Gamma’ class are not considered a miss for this metric. Consequently, the number of correct classifications from the automated Mount Wilson algorithm improves to 203 out of 229 (88.6%) for the two month analysis period. In a sense, this metric states that the automated Mount Wilson classification algorithm is assigning a reasonable magnetic classification almost 9 out of 10 times, and again, this performance metric should improve with tweaks to the magnetic parameters utilized.

4.7.2. Follow-up Adjustments and Results

Additional analysis has been conducted in order to isolate causes as to why the research code output is differing from SWPC magnetic classifications. To do so, a larger data set is applied to this analysis, spanning 1 January 2015 through 31 May 2015. The same magnetic classification algorithm described above was applied to this new data span resulting in a direct match of 67.26% and a relaxed match of 85.93%. Changes to the algorithm described below will seek to improve upon these two percentages.

The first step in improving the Mount Wilson algorithm is to identify parameters that will adequately distinguish the differences between the automated research code

output and SWPC magnetic classifications. It was determined that comparing the area of each sunspot group in MoSH to the separation distance between the two magnetic polarity regions in heliographic degrees identifies such a difference between the two data sources. Figure 19 demonstrates the comparison between area and separation distance for sunspot groups that were given a ‘Beta’ classification by SWPC and Figure 20 demonstrates the same comparison for magnetic classifications assigned by the automated SDO research code. Differences between these two figures illustrate two instances where the two classification schemes are diverging, highlighted by the red circles in Figure 19 and Figure 20.

The red circle in Figure 19 depicts sunspot groups of relatively large size that were measured to have a relatively small separation between areas of opposite magnetic polarity. One of the initial assumptions when creating the Mount Wilson magnetic classification algorithm was that these types of spot groups would fall into the ‘Beta-Gamma’ category. Note the absence of these groups in Figure 20. Additionally, the red circle in Figure 20 is highlighting sunspot groups of relatively large area and magnetic separation that were given a ‘Beta’ classification by the automated SDO code but were identified as ‘Beta-Gamma’ by SWPC magnetic classifications.

The Mount Wilson algorithm within the automated SDO code was adjusted so that sunspot groups falling into the two categories described above are given a magnetic classification aligned with the SWPC classification. However, the same classification rules as before are applied to sunspot groups falling outside those two circles. Figure 21 demonstrates the new output of the research code when run for the 1 January 2015 through 31 May 2015 data set with the adjusted classification rules. The result is a distribution that better matches the SWPC distribution in Figure 19. With these adjustments in place, the direct metric improved to 75.48% and the relaxed metric improved to 87.4%. By making these adjustments, the Mount Wilson algorithm is now built, at least in part, to match SWPC classification methods. As a result, any bias in the

SWPC magnetic classification method could very well show itself in this automated empirical method. This is an accepted outcome since explicit interpretation of the Mount Wilson magnetic classification rules for an automated code is not possible. Matching with a reliable classification source, such as SWPC, is considered a positive result in this instance.

One final adjustment was considered. The Mount Wilson algorithm up to this point will assign sunspot groups a magnetic classification of ‘Gamma’ for instances when the separation between polarity regions is small compared to the overall extent of the polarity region, as described in Section 3.6. However, not once in the three years of data since the start of Spahr’s analysis did SWPC assign the ‘Gamma’ classification. As such, it is impossible to test whether this assumption about the magnetic characteristics of a ‘Gamma’ sunspot group are accurate. Despite creating conditions for the ‘Gamma’ classification to be assigned sparingly, there were 23 instances when the automated code assigned a ‘Gamma’ or ‘Gamma-Delta’ classification over this five month period. It was desired to include the ‘Gamma’ outcome in search of a complete Mount Wilson magnetic classification algorithm. Removing this outcome and reanalyzing the data produced a direct match of 79.78% and a relaxed match of 91.74%. Both metric values improved, but the result is a Mount Wilson algorithm that can only assign five out of the seven possible Mount Wilson classifications. Future utilization of this code should consider analyzing additional data sets for determination of magnetic parameters that can adequately identify ‘Gamma’ type sunspot groups.

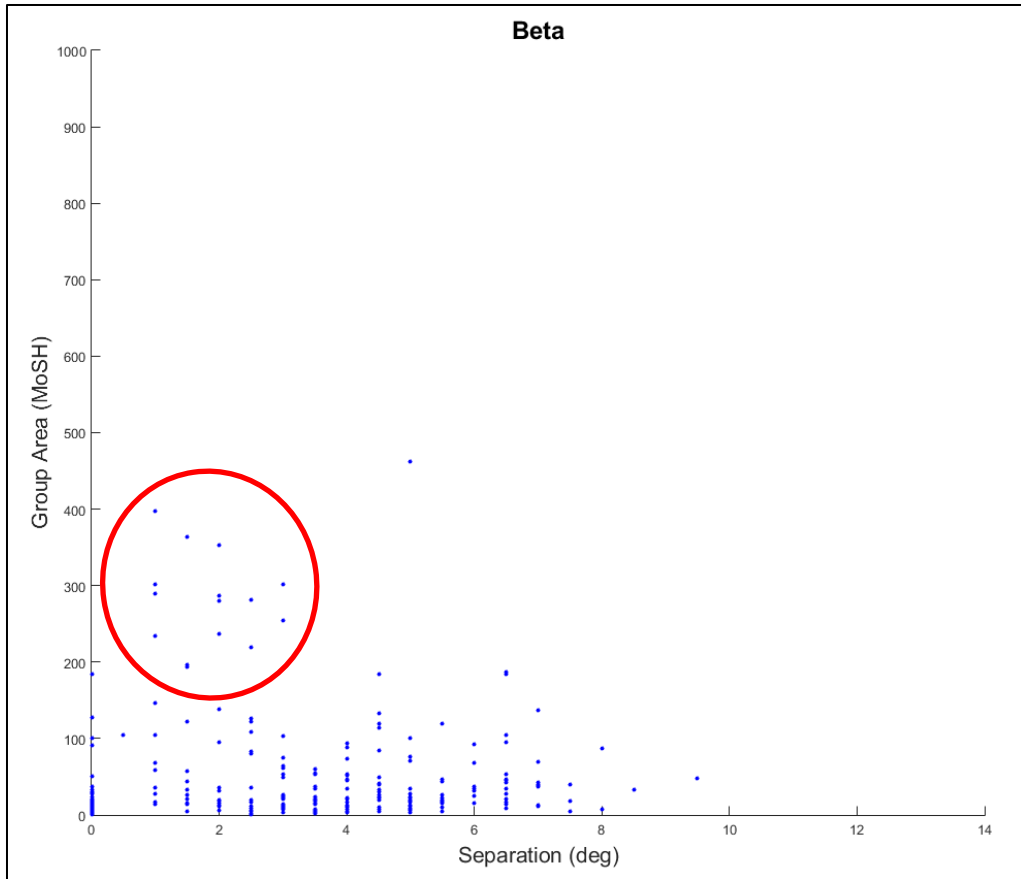


Figure 19. SWPC Group Area Comparison with Magnetic Separation. The plot compares group area in MoSH to magnetic separation in degrees for sunspot groups given a ‘Beta’ classification by SWPC for 1 January 2015 through 31 May 2015. The red circle highlights sunspot groups that do not appear in Figure 20.

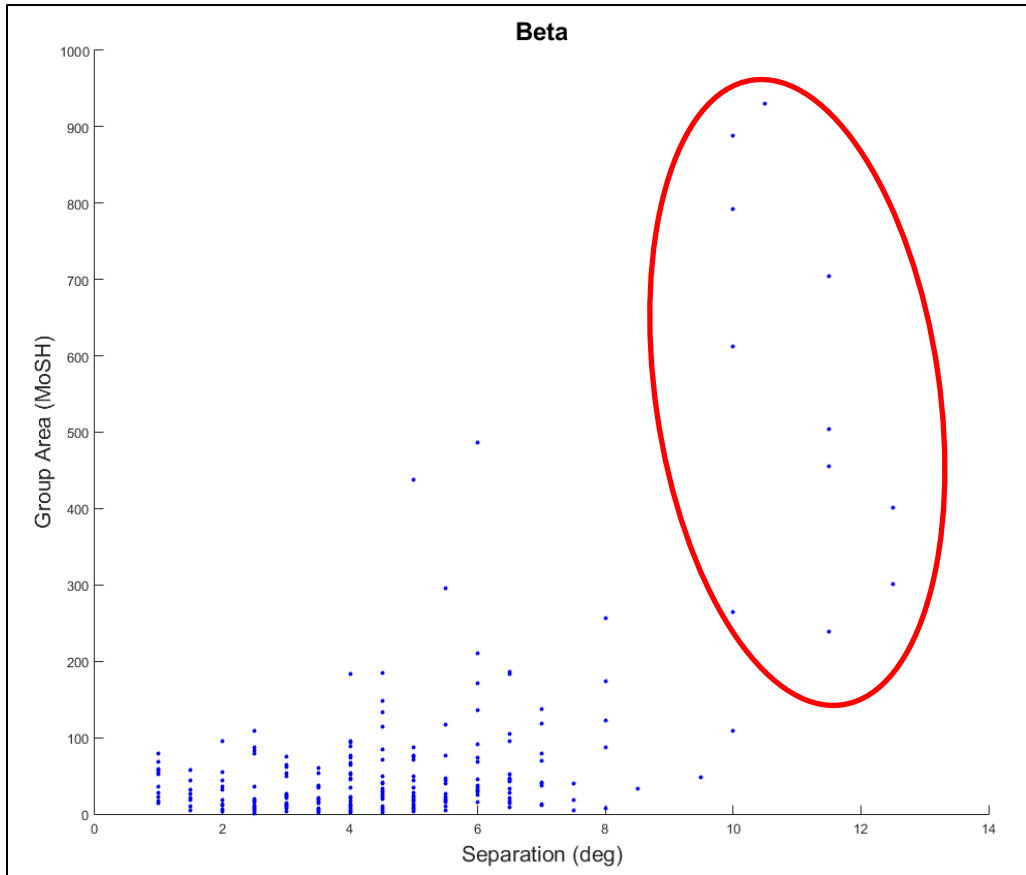


Figure 20. SDO Group Area Comparison with Magnetic Separation. The plot compares group area in MoSH to magnetic separation in degrees for sunspot groups given a ‘Beta’ classification by the automated SDO research code for 1 January 2015 through 31 May 2015. The red circle highlights sunspot groups that do not appear in Figure 19.

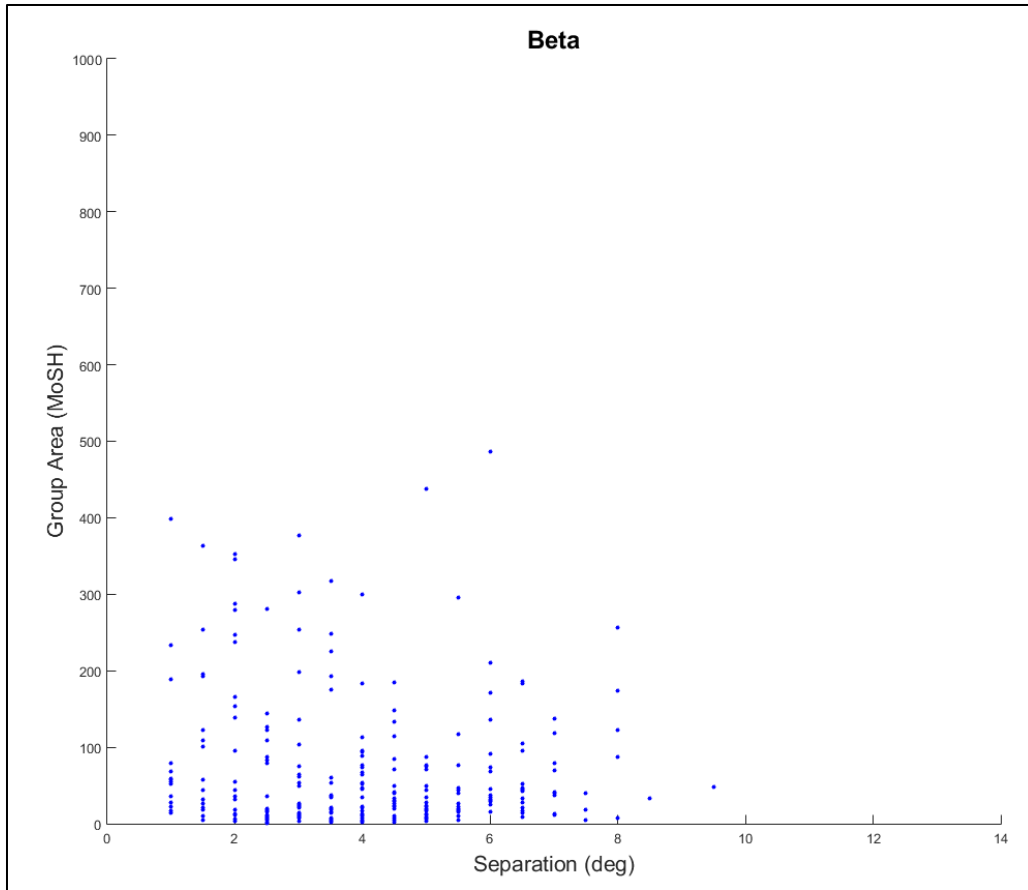


Figure 21. Adjusted SDO Group Area Comparison with Magnetic Separation. The plot compares group area in MoSH to magnetic separation in degrees for sunspot groups given a ‘Beta’ classification by the adjusted automated SDO research code for 1 January 2015 through 31 May 2015. The distribution of sunspot groups in this figure better matches that of Figure 19 indicating that the adjusted automated code is a closer match to SWPC magnetic classification methods.

V. Conclusions

5.1 Summary of Results

SDO/HMI imagery for the period of 1 July 2013 through 31 July 2015 was analyzed using the automated sunspot analysis code created by Spahr (2014). The code utilizes full-disk HMII and HMIB images to first detect solar sunspots by correcting for limb darkening and then isolating sunspots through use of a thresholding routine. Next the individual sunspots are systematically grouped together and classified according to the McIntosh classification rules (McIntosh, 1990). Results of the analysis are compared against sunspot data recorded by NOAA's Space Weather Prediction Center (SWPC). Regression analysis between sunspot area, number of groups, and number of sunspots over the 25 month research period yields results consistent to those found by Spahr (2014) for the time period of 1 July 2012 through 30 June 2013. Using the three-tiered McIntosh comparison metric devised by Spahr (2014) to compare data from the automated research code to SWPC sunspot data, the new analysis period for his research achieved a 18.09% 'direct' match, a 49.5% 'intermediate' match, and a 81.31% 'relaxed' match. Comparison results showed statistical confidence that this automated classification code is expected to perform consistently for future utilization.

In addition to conducting the same analysis of Spahr (2014) for the additional data period, a feature tracking algorithm and Mount Wilson Magnetic Classification scheme were added to the existing code so that output of the research code matches the full-spectrum sunspot characterization as utilized by manual solar observing entities such as SPWC and USAF solar observation units. The feature tracking algorithm utilizes existing information from the detection and classification stages of the research code to compare the predicted future placement of sunspot groups, based upon known solar rotation rates, to the actual observed locations at that future time. Matched groups are assigned the same

tracking number for the entirety of the sunspot group's lifetime. Tracking number assignment proved very accurate at time scales out to four days between consecutive SDO images. The Mount Wilson algorithm added to the research code assigns each sunspot group one of five unique magnetic classifications by comparing magnetic information from the HMIB Magnetogram image to sunspot group extent. Derived magnetic parameters were used to analyze five months of data, 1 January 2015 through 31 May 2015. Results attained a 79.78% direct match with SWPC magnetic classifications and a 91.74% relaxed match.

5.2 Operational Implementation

Operational implementation of this research code, or similar automated sunspot analysis code, would be considered a positive outcome for USAF space weather operations due to the increased ability to analyze vast amounts of solar imagery data. For this code to be implemented, it is advised that the following considerations be acknowledged up front. First, the research code was not created to match manual observations. As is noted above, direct match between the SDO analysis and SWPC data sets is rare for any of the measured quantities. As such, implementation of this code in its present form for operational purposes would immediately create inconsistency in record keeping between time periods that utilized manual observations and time periods using this automated code. Additionally, the code is built for SDO images at the 4096×4096 pixel resolution. Application of this research code to lower resolution imagery, including non-SDO Intensitygram and Magnetogram images, is certainly possible, but code output and comparison metrics would differ from that observed for this research (Howard, 2015). A testing period will be needed for inclusion of any new imagery source into code execution. Note that one of the benefits of using SDO imagery is the inherent high signal to noise ratio. Utilization of other imagery sources may require corrective measures to remove high levels of noise, as was experienced by Howard (2015).

Successful implementation of this code would likely embody only partial utilization of the code for operational decision making. In a sense it could be a good first analysis for manual observers, providing a means for further refining the observation process. However, the original intent of the code was to provide a research tool for further analysis of solar activity. The code is built to analyze many images at a time allowing for the production of a database of sunspot analysis going back as far as solar imagery will allow.

5.3 Future Work

The first recommended update for this research is improvement of the Mount Wilson algorithm. The magnetic classification scheme described in Chapter III and Chapter IV was devised empirically based upon a small sample size due to time limitations with this research. A larger testing period should be applied to the Mount Wilson algorithm, allowing for the specified magnetic parameters to be narrowed down further with possible implementation of additional parameters for the more accurate magnetic classification assignment. If possible, data necessary for determining parameters necessary to assigning a ‘Gamma’ classification should be sought out. The current algorithm can only assign five out of seven Mount Wilson magnetic classifications

Lastly, the primary intention of this research is to provide a means for further analysis of sunspot group growth or decay as a lead up to other major solar activity to include solar flares and coronal mass ejections (CMEs). Predictive ability for these major solar phenomena is of great concern to the USAF but is still limited in scope. This area of research would likely require hammering down typical growth and decay trends for McIntosh classifications or even Mount Wilson magnetic classifications, and then comparing those typical trends to trends seen in the lead up to major solar eruptions. As such, the researcher tackling this objective will need a reliable database of solar flare or

CME data that correlates the solar eruption to a specific active region or sunspot group. SWPC maintains record of such events, though other databases may exist that provide more robust information. Similar research comparing the point-in-time McIntosh classifications to solar flare occurrence has previously been conducted. However, utilization of an automated code with high spatial and temporal resolution imagery that incorporates the varying structure of the sunspot group over time to determine the likelihood of explosive solar activity seems like a worthy continued avenue of research.

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