A NEW METHOD TO QUANTIFY X-RAY SUBSTRUCTURES IN CLUSTERS OF GALAXIES

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ABSTRACT

We present a new method to quantify substructures in clusters of galaxies, based on the analysis of the intensity of structures. This analysis is done in a residual image that is the result of the subtraction of a surface brightness model, obtained by fitting a two-dimensional analytical model (β-model or Sérsic profile) with elliptical symmetry, from the X-ray image. Our method is applied to 34 clusters observed by the Chandra Space Telescope that are in the redshift range \( z \in [0.02, 0.2] \) and have a signal-to-noise ratio \((S/N)\) greater than 100. We present the calibration of the method and the relations between the substructure level with physical quantities, such as the mass, X-ray luminosity, temperature, and cluster redshift. We use our method to separate the clusters in two sub-samples of high- and low-substructure levels. We conclude, using Monte Carlo simulations, that the method recuperates very well the true amount of substructure for small angular core radii clusters (with respect to the whole image size) and good \( S/N \) observations. We find no evidence of correlation between the substructure level and physical properties of the clusters such as gas temperature, X-ray luminosity, and redshift; however, analysis suggest a trend between the substructure level and cluster mass. The scaling relations for the two sub-samples (high- and low-substructure level clusters) are different (they present an offset, i.e., given a fixed mass or temperature, low-substructure clusters tend to be more X-ray luminous), which is an important result for cosmological tests using the mass–luminosity relation to obtain the cluster mass function, since they rely on the assumption that clusters do not present different scaling relations according to their dynamical state.

Key words: galaxies: clusters: general – galaxies: clusters: intracluster medium – large-scale structure of universe – X-rays: galaxies: clusters

Online-only material: color figures

1. INTRODUCTION

Clusters of galaxies are the largest virialized objects in the universe, the upper limit of collapsed halo mass function. In a universe dominated by a cosmological constant and cold dark matter (ΛCDM), dark matter halos are formed by gravitational instability from primordial quantum fluctuations in the mass density field. The amplitude of those fluctuations increases as they cease expanding with the Hubble flux, collapse, and virialize, forming dense and relaxed structures. Smaller structures grow to larger ones through mergers, up to clusters of galaxies in the present time. In this hierarchical scenario of structure formation, clusters are thus dynamically young objects and contain evidence of their recent past merging history (e.g., Kauffmann & White 1993). We can relate substructures with the cluster dynamical age (e.g., Richstone et al. 1992; Suwa et al. 2003): the more substructure (their total intensity) a cluster presents, the younger (dynamically speaking) it is.

The hot intracluster plasma is a powerful X-ray source and its observation reveals the projected spatial distribution of most of the baryonic mass. X-ray studies of galaxy clusters are thus particularly relevant in this context, as they can give us clues to the dynamical age of clusters (e.g., Henriksen et al. (2000)—A3266; Lima Neto et al. (2003)—A970; Ferrari et al. (2005)—A3921). Analysis of substructure in the intracluster plasma spatial distribution should help us determine the dynamical state of galaxy clusters. A very good review about the theory and observational status of the study of substructures based on X-ray data in clusters of galaxies is given by Jeltema et al. (2005). Here, we only briefly discuss some of the previous work on cluster substructures.

Jones & Forman (1992) made the first X-ray systematic study of structures in galaxy clusters, visually analyzing 208 objects observed by the Einstein satellite, establishing that merging must be a common phenomenon in clusters. Richstone et al. (1992) developed in an original theoretical study a relation between substructures and cosmology, where they put constraints on cosmological parameters by the fractional rate of major mergers in clusters.

X-ray surface brightness allows us to perform statistical tests such as centroid and ellipticity variation (Mohr et al. 1995), relating the dynamical age of clusters with its morphology. Buote & Tsai (1995, 1996) developed a method to quantify X-ray substructures in clusters of galaxies from the moments of the expansion in Fourier series of the X-ray surface brightness. Jeltema et al. (2005) used the same method, referred to as the power-ratio method, in a sample of 40 clusters of galaxies observed by Chandra. They showed that clusters in general are less relaxed at \( z > 0.5 \) than at \( z \approx 0 \).

Semianalytic methods give an indication of the expected evolution of cluster substructure and its dependence on cosmological parameters; however, the best method of constraining cosmological models is probably through the comparison with hydrodynamic cluster simulations (Valdarnini et al. 1999; Suwa et al. 2003). For instance, Suwa et al. (2003) compared simulated clusters in a ΛCDM and an OCDM cosmology, at both \( z = 0 \) and \( z = 0.5 \), using several methods for quantifying structure. They restrict themselves to comparing the ability of different statistical indicators in distinguishing different simulated cosmologies, showing that cluster structure can potentially constrain \( \Omega_\Lambda \) or the dark energy equation of state.
3.1. Data Reduction

We have used the package CIAO 3.4. Initially a level-2 event file has been generated from a level-1 event file, using the standard pipeline procedure\footnote{http://cxc.harvard.edu/ciao3.4/threads/createL2/} and the calibration files, CALDB 3.3.0. Periods with high particle background (flares) were excluded using the lc\_clean script. At this point, a re-binned image with pixels corresponding to 16 raw physical pixels (4 × 4, which roughly corresponds to 2'' pixels) is created from the new level-2 event file, in the energy band 0.3–7.0 keV. Then, we produce exposure maps and use them to obtain flat images from which the source points are removed by filling circles around each source with a random Poisson sampling with the same distribution as found in a circular region close to the source. Finally, we fit a two-dimensional analytical surface brightness model.

3.2. Surface Brightness

The surface brightness profile is the projection of the plasma emissivity along the line of sight. We will assume two radial analytical profiles for the surface brightness: the β-model (Cavaliere & Fusco-Femiano 1976) and the Sérsic (Pislar et al. 1997; Demarco et al. 2003).

In order to take into account the ellipticity of the plasma emission we use the following standard coordinates transformation:

\[
\begin{align*}
    x' &= (x - x_0) \cos \theta - (y - y_0) \sin \theta \\
    y' &= (x - x_0) \sin \theta + (y - y_0) \cos \theta \\
    r' &= x'^2 + y'^2,
\end{align*}
\]

where \((x_0, y_0)\) is the X-ray emission center coordinates, \(\theta\) is the position angle, and \(\epsilon\) is the ellipticity.

The β-model may now be defined as follows:

\[
\Sigma(r) = \Sigma_0 \left[ 1 + \left( \frac{r}{r_c} \right) ^ \beta \right] ^ {-3\beta+0.5} + b,
\]

where \(r_c\) is the core radius, \(\beta\) is the shape parameter, and \(\Sigma_0\) is the central surface brightness. The parameter \(b\) corresponds to the background and is supposed to be constant throughout the image (hence the importance of the exposure map correction).

The Sérsic model is defined as follows:

\[
\Sigma(r) = \Sigma_0 \exp \left[ -\left( \frac{r}{a} \right) ^ ν \right] + b,
\]

where \(a\) is the scale parameter, \(ν\) (often represented as 1/\(n\)) is the shape parameter, and \(b\) is again the background surface brightness.

Once we have the image correctly processed, we fit a two-dimensional surface brightness model to it using a standard minimum squares method, \(\chi^2\), and obtain the residual image, which is going to be the starting point for substructure quantification.

We fitted the β and Sérsic models for most of the clusters, and in the case where both models were fitted, we chose to use the one that gave the smaller substructure level (see below how the substructure level is defined and computed). In practical terms, this is the same as choosing the fit with the smallest \(\chi^2\). The two-dimensional surface brightness model fitted for each cluster is presented in Table 2.
4. X-RAY SUBSTRUCTURES

Previous studies on intracluster medium substructure have been done, either qualitatively (Jones & Forman 1984, 1992; Laganá et al. 2008, 2010) or quantitatively (Soltan & Fabriant 1990; Richstone et al. 1992; Buote & Tsai 1995; Jeltema et al. 2005), based on different techniques. There is, however, no method that takes into account the ratio between the number of counts on the residual and on the original images, which will be referred to as the residual flux method. We describe here this method to quantify the substructure on the intracluster plasma emission.

4.1. Substructure Level

We start by defining a threshold for the residual image in order to identify the pixels which had a number of counts statistically significant above or below (positive and negative residues) the two-dimensional surface brightness fitted model at the pixel position. The threshold in each pixel was defined as the square root of the number of counts of the model in the correspondent pixel, i.e., the expected variance. Then, we quantify the substructure level by computing the ratio between the total number of counts of the residual and the expected variance. The threshold in each pixel was defined as the square root of the number of counts of the model in the correspondent pixel, i.e., the expected variance.

We defined the substructure level this way because it has a direct physical interpretation: it reflects the fraction of the total X-ray luminosity provided by substructures.

The statistical uncertainties in the substructure level were computed using Monte Carlo simulations described in Section 5.4.

5. CALIBRATION OF THE METHOD

5.1. General Case

We may write Equation (1) as

$$S(t) = \frac{\sum_{i=1}^{n} |C_i(t) - M_i| \times t}{\sum_{i=1}^{n} |C_i - b_i| \times t},$$

where $M_i$ is the model fitted to the image, which is decomposed into the cluster surface brightness model and a constant background, i.e., $M' = M + b$.

The number of counts of the $i$th pixel, for a certain exposure time $t$, may be written as

$$C_i(t) = P [(b_i + S_1^i + S_2^i) \times t],$$

where $b_i$, $S_1^i$, and $S_2^i$ are the expected number counts in the $i$th pixel for an exposure time of $t = 1$, in an arbitrary time unit, from the background, primary cluster, and substructures, respectively. $P(x)$ is the random Poisson deviate of the expected value $x$. In the limit when $x \rightarrow t$, $P(x) \rightarrow t \pm t^{1/2}$.

By injecting Equation (3) in Equation (2) and taking into account that the sum of counts of the model is equal to the sum of counts of the main cluster plus substructures, i.e.,

$$\sum_{i=1}^{n} M_i = \sum_{i=1}^{n} (S_1^i + S_2^i),$$

we have

$$S(t) = \frac{\sum_{i=1}^{n} |(b_i + S_1^i + S_2^i) \times t - (M_i + b) \times t|}{\sum_{i=1}^{n} (S_1^i + S_2^i) \times t},$$

where $b$ is the mean background level, i.e., $b = \frac{1}{n} \sum_{i=1}^{n} b_i$.

5.2. Long Exposure Time Observation

We now consider the limit of a very long exposure time. In this case, $P[(b_i + S_1^i + S_2^i) \times t \rightarrow (b_i + S_1^i + S_2^i) \times t]$, so the Equation (4) takes the form

$$\lim_{t \rightarrow \infty} S(t) = \frac{\sum_{i=1}^{n} |S_1^i + S_2^i - M_i - (b_i - b)|}{\sum_{i=1}^{n} (S_1^i + S_2^i)}.$$

We may write the model as: $M_i = S_1^i + D_i$, where $D_i$ is the deviation on the $i$th pixel due to $S_2$ (the presence of substructures will change the model fitted in the $i$th pixel by $D_i$). Now Equation (5) takes the form

$$\lim_{t \rightarrow \infty} S(t) = \frac{\sum_{i=1}^{n} |S_2^i - D_i - (b_i - b)|}{\sum_{i=1}^{n} (S_1^i + S_2^i)},$$

which is different from the ideal case,

$$S' = \frac{\sum_{i=1}^{n} |S_2^i|}{\sum_{i=1}^{n} (S_1^i + S_2^i)},$$

in which the substructure level reflects exactly the fraction of counts provided by the substructures. However, using Monte Carlo simulations (which will be discussed in Section 5.4) to introduce substructure on model images of the clusters of the sample, one may correct this effect by introducing a normalization factor in Equation (6) for each cluster, allowing us to better estimate the true substructure level and quantify the systematic uncertainties involved in this method.

5.3. Short Exposure Time Observation

We consider now the limit when we have a very short exposure time. In this case the Poisson noise dominates over the systematic uncertainties involved in this method. We consider now the limit of a very long exposure time. In this case, $P[(b_i + S_1^i + S_2^i) \times t \rightarrow (b_i + S_1^i + S_2^i) \times t]$, so the Equation (4) takes the form

$$\lim_{t \rightarrow \infty} S(t) = \frac{\sum_{i=1}^{n} |S_1^i + S_2^i - M_i - (b_i - b)|}{\sum_{i=1}^{n} (S_1^i + S_2^i)},$$

we now consider the limit of a very long exposure time. In this case, $P[(b_i + S_1^i + S_2^i) \times t \rightarrow (b_i + S_1^i + S_2^i) \times t]$, so the Equation (4) takes the form

$$\lim_{t \rightarrow \infty} S(t) = \frac{\sum_{i=1}^{n} |S_1^i + S_2^i - M_i - (b_i - b)|}{\sum_{i=1}^{n} (S_1^i + S_2^i)}.$$
The substructures added to the analytical images had surface brightness described by a $\beta$-model, with core radii and central surface brightness intensities that could vary between 25% and 75% of the modeled cluster, the exact value being determined by a random variable. The number of substructures could also vary from 0 (i.e., no substructure) to 3.

In order to show that, basically, the quality of the substructure quantification depends on the size of the cluster compared to the whole image and the S/N, we present Figure 4, which shows how the corrected substructure level compares to the true values for different cluster configurations in which different synthetic clusters were created, with fixed $\beta = 2/3$, core radius spanning from 20 to 80 pixels (whole image is $500 \times 500$ pixels), and S/Ns varying from 100 to 700. We see in the left bottom plots that when substructures are close to the center of the clusters the method does not give a reliable result since the substructure is incorporated into the model when the surface brightness fit is performed. Therefore, small angular core radii tend to give better results since the amount of substructure which falls within the clustercentric distance is small.

First, we made a linear fit of the measured substructure level against the true substructure level, i.e., for each cluster we had a relation: $S_M = a + b \times S_T$, where $S_M$, $S_T$, $a$, and $b$ are the measured and true substructure levels, linear, and angular coefficients, respectively. Once the fit was done, the corrected substructure level was computed using $S_C = (S_M - a)/b$.

In Figure 6, we see the measured substructure level plotted against the true substructure level on the left panel and then the correction plotted on the center panel.

The error bars were determined from the points distribution shown in Figure 5. Starting with the cluster corrected substructure level, $S_C$, we defined a symmetrical region $S_C \pm \delta S_C$ (horizontal dashed lines in Figure 5) where we have at least 18 data points\(^2\) in each side with respect to $S_T - S_C = 0$. Then, the asymmetrical error bars correspond to the range of 68% of the points in each side separately (red points in Figure 5).

In Figure 6 we present the calibration for some (four) clusters of the sample, which were chosen because they represent different levels of substructure (from A907 with $S_C = 0.062$ to A2163 with $S_C = 0.155$) and different core radii and S/N. This figure shows both those measured against the true substructure level (central panel), and the method we used for computing the uncertainties on the substructure quantification (right panel). Figure 7, we illustrate the Monte Carlo simulation with a very small sub-sample of the images created to calibrate the method for A85. On the top left we see its X-ray image, as observed by the Chandra Space Telescope, and its simulated images containing randomly distributed substructures.

6. RESULTS AND DISCUSSION

Now that we have measured and corrected the substructure level and estimated the error bars within 68% confidence level
using Monte Carlo simulations, we may look for correlations between the substructure level, as we defined, and physical properties of the clusters.

For correlations to be correctly assessed, it is necessary to understand well how variables are related. Linear regression is a fundamental and frequently used tool in astronomy and it may seem surprising that such an apparently simple statistical procedure may be complicated and controversial (see, e.g., Isobe et al. 1990; Feigelson & Babu 1992; Hogg et al. 2010, for reviews). Briefly, when the scientific question clearly asks how one variable depends on the other, it is more appropriate to use OLS($Y|X$), ordinary least square—the least square fit of the function $Y(X)$—to quantify how the variables are correlated, with $Y$ being the dependent variable. However, when the scientific question does not clearly identify the dependent variable, then the use of OLS (bisector), which is the bisector between the OLS($Y|X$) and OLS($X|Y$) fits, the last case representing the fit inversion with respect to the variables, is recommended.

**Figure 4.** Illustration of the sensitivity of the method. For each plot we have the corrected ($S_c$) against the true substructure level ($S_T$) for each of the 200 simulated images. Each plot corresponds to different signal-to-noise ($S/N$) and core radii ($R_c$) simulated clusters, with $R_c$ given in pixels. The simulations were performed in 500 × 500 pixels images (see Figure 7). For comparison, the dashed lines represent the 1:1 relation between the corrected substructure level against the actual value.

**Figure 5.** Illustration on how the uncertainties on the substructure level are computed. (A color version of this figure is available in the online journal.)
used (Feigelson & Babu 1992) to fit the data and estimate the uncertainties. Different resampling methods such as Jackknife or Bootstrap should be used (Feigelson & Babu 1992) to fit the data and estimate the uncertainties.

There are many contributions from complicated variables. In the context. A correlation of 0.9 may be very low if we are verifying a physical law with high-quality equipments, but may be seen as very high in social sciences, for example, where there are many contributions from complicated variables. In Table 1, we give the two-tailed null hypothesis significance for each Pearson correlation coefficient (see Press et al. 1992 for more information on how it is computed).

In our case, we used the OLS(\(Y|X\)) to fit relations between the substructure level and physical parameters, whereas we used the OLS (bisector) for the scaling relations; all fits were performed using the Jackknife resampling method.

### 6.1. Clusters Parameters

In Table 2 we give the corrected substructure level (\(S_c\)), \(M_{500}\), X-ray luminosity, temperature, redshift, the two-dimensional analytical surface brightness model fitted, core radius (\(R_c\)), and S/N of the 34 clusters of the sample.

We computed the substructure level and the two-dimensional analytical surface brightness model, while other parameters were obtained from the literature (Reiprich & Böhringer 2002; Sun et al. 2004; Chen et al. 2007; Maughan et al. 2011). \(M_{500}\) and X-ray luminosity were corrected to a Hubble constant of 70 km s\(^{-1}\) Mpc\(^{-1}\), and then X-ray luminosity was extrapolated to the bolometric band (0.01–100 keV) using K-correction and the XSPEC 12.0 MEKAL model (Mewe–Kaastra–Leidahl plasma emission code), since literature values were given for different Hubble constants and energy bands. Redshifts were obtained from NED (NASA/IPAC Extragalactic Database) with uncertainties varying from 10\(^{-6}\) to 10\(^{-4}\), and therefore as they are extremely small compared to other uncertainties we use, they are not displayed in Table 2.

### 6.2. Substructure Level versus Physical Parameters

Keeping in mind the different statistical approaches, for all the correlations between the substructure level and physical parameters the OLS (\(Y|X\)) was used, since the substructure level may depend on mass, temperature, and luminosity but these quantities should not be dependent on substructure in the way it was defined. For the scaling relations we used the OLS (bisector) since temperature, luminosity, and mass have complicated relations connecting them. For instance, mass is one of the quantities that determines the cluster temperature, but temperature is used to compute the mass. Luminosity is the observed quantity (flux and redshift), although it depends on temperature. Therefore complicated relations exist among them, which made us use OLS (bisector). On the other hand, concerning the data size, since we have used 34 data points we chose the Jackknife resampling method to perform all the fits. The results of the fits are presented in Table 1.

### 6.2.1. Substructure Level versus Redshift

Figure 8 shows the substructure level as a function of cluster redshift. We see that there is a dependence between the substructure level and redshift (\(S \propto (1 + z)^{5.45 \pm 1.95}\)), although within 2.8\(\sigma\) we find no evolution at all in the substructure level. The dependence on redshift may be explained by the fact that nearby clusters fill a larger detector area compared to more distance clusters, and as explained in the calibration section (Section 5), they tend to underestimate the substructure level, since substructures that lie within small clustercentric distances are incorporated into the surface brightness fit and are hardly quantified. Furthermore, the Pearson correlation coefficient of 0.35 shows us a weak correlation, which translates to no significant structural evolution of the gas distribution. We also note the strong scatter of the data points in the redshift range \(z \in [0.02, 0.2]\), showing that we find clusters in very different dynamical states in this redshift interval, from those...
Figure 6. Illustration of the calibration applied to some clusters of the sample. Left: measured substructure, $S_M$, vs. the true substructure level, $S_T$, for all 200 Monte Carlo simulations. Center: corrected substructure, $S_C$, vs. true substructure level for all simulations. Right: substructure corrected vs. (true substructure level−corrected substructure) for the simulations. We only show examples for four clusters. See the text for details on the corrections made. For comparison, the lines represent the 1:1 relation between the measured and corrected substructure level against the actual value.

(A color version of this figure is available in the online journal.)

highly symmetrical to the very disturbed ones (see Figures 9 and 10). Such a scatter may be related to the young (dynamically speaking) age of massive clusters. A4038, which has the smallest substructure level, has been considered in all fits; however, we present in Figures 8 and 11–13 dashed lines representing the fits excluding it, since one could ask how much influence it has in determining the slopes of the curves.

Computing a temperature map based on Chandra data, Markevitch & Vikhlinin (2001) clearly showed that the A2163 cluster (see Figure 10) is undergoing a major merger, which explains its high-substructure level ($SL = 0.155^{+0.025}_{-0.024}$).

6.2.2. Substructure Level versus Temperature

We see in Figure 11 that hotter clusters show tendency to present more substructures; however, the Pearson coefficient of 0.36 shows a weak correlation. The slope of $0.74 \pm 0.30$ shows a positive correlation within $2.5\sigma$; however, the weak correlation
does not allow us to state any firm conclusion concerning the intensity of substructures and gas temperature enhancements.

6.2.3. Substructure Level versus Luminosity

We see in Figure 12 that substructure is basically independent of X-ray luminosity, with the Pearson coefficient of 0.26 being the lowest between the substructure level and the physical parameters. Furthermore, the substructure level is compatible with no dependency at all on the X-ray luminosity within only 1.7σ.

6.2.4. Substructure Level versus Mass

Figure 13 shows the substructure level as a function of the cluster mass. We see that more massive clusters have a tendency to present more substructures. The relation between the substructure level and the mass has the form $S \propto M^{0.62\pm0.20}$, with a positive correlation within 3.1σ; however, as opposed to correlations of the temperature, luminosity, and redshift with the substructure level, the Pearson correlation coefficient is the largest (0.49) between them, presenting a strong (null hypothesis significance = 0.003265—there is only ~0.3% probability of not presenting correlation) relation between the amount of substructures a cluster presents and its mass.

6.3. Scaling Relations

Chen et al. (2007) constructed two cluster samples based on the intracluster plasma central temperature, and they concluded

Figure 8. Substructure level evolution. Solid and dashed lines correspond to the fit using all 34 clusters, and excluding A4038 (the cluster with $S_C < 0.004$, on the bottom left of the plot), respectively. The fit with all clusters is given by $SL = 0.036^{0.011}_{0.005} \times (1+z)^{4.5\pm1.5}$, where we used the OLS $F(X)$. The Pearson correlation coefficient obtained was 0.35.
Figure 9. A4038, a symmetric cluster, with few substructures. The substructures are basically due to the ACIS-I chip gaps, which represent only a very small fraction of the total counts ($S_C = 0.004$).

(A color version of this figure is available in the online journal.)

Figure 10. A2163, a perturbed cluster, with asymmetries and substructures ($S_C = 0.155$).

(A color version of this figure is available in the online journal.)

Figure 11. Substructure level vs. temperature. For explanation of the fits, see caption of Figure 8. The solid line is given by $SL = 0.016^{+0.012}_{-0.005} \times kT^{0.74 \pm 0.30}$, where the fits performed was the OLS $Y(X)$ and the Pearson coefficient obtained was 0.36.

Figure 12. Substructure level vs. luminosity. For explanation of the fits, see caption of Figure 8. The solid line is given by $SL = 0.040^{+0.014}_{-0.010} \times L_X^{0.17 \pm 0.10}$. The fits performed was the OLS $Y(X)$. The Pearson coefficient obtained was 0.26.
that cooling-core clusters have different scaling relations compared to non-cooling-core clusters. Using the same idea, we created two different groups based on the substructure level. We computed the mean and median substructure level of the sample (illustrated in Figure 14). We choose the median, which is more robust when it comes to extreme data points, as a division line between the high- and low-substructure levels. Therefore, clusters were separated into two sub-groups according to their substructure level compared to the median value of the whole sample. Numerically, a cluster was considered highly substructured if its substructure level were greater than $S = 0.069755$, and a low-substructure level cluster otherwise.

The cluster segregation in the high- and low-substructure levels shows that hotter clusters are distributed equally between the high- and low-substructure level clusters, and the more massive and luminous clusters do not reside in any preferred group (high- and low-substructure groups).

The Pearson correlation strength coefficients for the scaling relations of these different groups are very similar, with the correlations for the high-substructure group being slightly
The Astrophysical Journal, 746:139 (13pp), 2012 February 20

Andrade-Santos, Lima Neto, & Laganá

Figure 13. Substructure level dependency on mass. For explanation of the fits, see caption of Figure 8. The solid line is given by \( SL = 0.021^{+0.010}_{-0.007} \times M_{500}^{0.62_{-0.20}^{+0.02}} \), where the fits performed was the OLS \( Y(X) \) and the obtained Pearson coefficient was 0.49.

Figure 14. Substructure level distribution of clusters.

higher (roughly 0.01 above). The slopes are very similar also, with the exception of the \( M-T \) relation being 1.23\( \sigma \) compatible, while the \( L-T \) and \( L-M \) relations are 0.53\( \sigma \) and 0.40\( \sigma \) compatible, respectively. However, as opposed to Figure 15 in which the slope is similar and the intercept offset between the curves is small, Figures 16 and 17 show a clear offset (2.07\( \sigma \) and 2.23\( \sigma \) for \( L-M \) and \( L-T \), respectively) between the curves for the high- and low-substructure level clusters. It appears that given a fixed cluster temperature or mass, the luminosity expected for low-substructure clusters tend to be higher. A possible explanation may be that low-substructure clusters, and therefore more relaxed ones, have had enough time for the gas to accumulate into the gravitational potential and become denser, thus enhancing the X-ray luminosity. Figure 6 of Chen et al. (2007) shows a very similar effect, where their cool-core clusters present higher X-ray luminosities for a fixed temperature, compared to non-cool-core clusters, which would favor low-substructure clusters, and therefore more relaxed ones, being associated with cool-core clusters.

Figure 15. Mass vs. temperature. In red (triangles) and blue (circles) are the high- and low-substructure level clusters, respectively. The red (dashed) and blue (solid) lines are the best fit for the high- and low-substructure level clusters, respectively. The fit of the low-substructure clusters is given by \( M_{500} = 0.37^{+0.079}_{-0.065} \times kT^{1.49_{-0.10}^{+0.10}} \), where the fit performed was the OLS (bisector) and the Pearson coefficient obtained was 0.92. On the other hand, the high-substructure level cluster fit is given by \( M_{500} = 0.312^{+0.039}_{-0.036} \times kT^{1.64_{-0.07}^{+0.07}} \) with a Pearson coefficient of 0.94.

(A color version of this figure is available in the online journal.)

Figure 16. Luminosity vs. temperature. See Figure 15 for information on the different points and lines. The fit of the low-substructure clusters is given by \( L_X = 0.058^{+0.025}_{-0.023} \times kT^{5.02_{-0.18}^{+0.18}} \), where the fit performed was the OLS (bisector) and the Pearson coefficient obtained was 0.90. On the other hand, the high-substructure level cluster fit is given by \( L_X = 0.029^{+0.013}_{-0.009} \times kT^{3.20_{-0.29}^{+0.29}} \) with a Pearson coefficient of 0.91.

(A color version of this figure is available in the online journal.)

The different scale relations between low–high-substructure level clusters suggests that substructures are an important factor...
clusters tend to be more X-ray luminous), which is an important result for cosmological tests which use the cluster-mass–luminosity relation to compute the mass function.

A practical application of our method would be the identification of clusters of very low substructure level. Such relaxed clusters would be ideal laboratories for studies where the equilibrium hypothesis is of paramount importance. As an example, the work of Bertolami et al. (2007), on the interaction between dark matter and dark energy, made use of the Layzer–Irvine equation, which must hold for a system in virial equilibrium when there is no interaction in the dark sector. They applied their method to A586, based on the analysis of Cypriano et al. (2005), which suggests that A586 is indeed a very relaxed cluster.

Finally, it is important to mention that the method itself is interesting since it concerns a new way to quantify substructures in clusters of galaxies, with a very simple physical interpretation: it reflects the fraction of the X-ray luminosity provided by substructures.

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7. CONCLUSIONS

We have developed a new method to quantify X-ray substructures in clusters of galaxies based on the ratio between the number of counts in the residual and original X-ray images. We calibrated the method and then applied it to 34 clusters of galaxies in order to obtain the substructure level dependence on physical parameters, such as mass, temperature, X-ray luminosity, and redshift.

The calibration was done using Monte Carlo simulations, which showed that the method recuperates very well the true amount of substructure for small angular core radii clusters (with respect to the whole image size) and good S/N observations.

The high scatter in the substructure level (spanning from less than 1% to ≃16%) in the redshift range $z \in [0.02, 0.2]$ shows that clusters are found in all dynamical states in the local universe, from those relaxed to those completely disturbed.

We have not found any strong evidence of correlation between the substructure level and physical properties of the clusters, gas temperature, X-ray luminosity, and redshift. However, there seems to be a correlation between the substructure level and the cluster mass, which is given by its Pearson correlation coefficient of 0.49. For our sample of 34 clusters it represents a probability of not presenting correlation of the order of 0.3%.

The distinction between high- and low-substructure level clusters is interesting, since different scaling relations were found with these two sub-samples (they present an offset of $\sim 2\sigma$—given a fixed mass or temperature, low-substructure

Figure 17. Luminosity vs. mass. See Figure 15 for information on the different points and lines. The fit of the low-substructure clusters is given by $L_X = 0.424^{+0.145}_{-0.105} \times M_{500}^{2.03^{+0.15}_{-0.10}}$, where the fit performed was the OLS (bisector) and the Pearson coefficient obtained was 0.88. On the other hand, the high-substructure level cluster fit is given by $L_X = 0.281^{+0.069}_{-0.065} \times M_{500}^{1.24^{+0.17}_{-0.15}}$ with a Pearson coefficient of 0.89. (A color version of this figure is available in the online journal.)

biasing scaling relations, and therefore it may affect the determination of mass clusters and thus the mass function that is used to test cosmological models, e.g., using the Press–Schechter Extended model, etc.
Reiprich, T. H., & Böhringer, H. 2002, ApJ, 567, 716
Richstone, D., Loeb, A., & Turner, E. L. 1992, ApJ, 393, 477
Rodgers, J. L., & Nicewander, W. A. 1988, Am. Stat., 42, 59
Soltan, A., & Fabricant, D. G. 1990, ApJ, 364, 433
Sun, M., Forman, W., Vikhlinin, A., et al. 2004, ApJ, 612, 805
Suwa, T., Habe, A., Yoshikawa, K., & Okamoto, T. 2003, ApJ, 588, 7
Valdarnini, R., Ghizzardi, S., & Bonometto, S. 1999, New Astron., 4, 71