Dynamic evolution of sentiments in Never Let Me Go: Insights from multifractal theory and its implications for literary analysis

Qiyue Hu, Bin Liu, Mads Rosendahl Thomsen, Jianbo Gao, Kristoffer L Nielbo

Dynamic evolution of sentiments in *Never Let Me Go*: Insights from multifractal theory and its implications for literary analysis

Qiyue Hu [1,2], Bin Liu [1,3], Mads Rosendahl Thomsen [4], Jianbo Gao [1,3]*, Kristoffer L. Nielbo [5]*
[1] Institute of Complexity Science and Big Data Technology,
Guangxi University, Nanning, Guangxi, China
[2] College of Chinese Language and Literature, Guangxi University, Nanning, Guangxi, China
[3] Business School, Guangxi University,
Nanning, Guangxi, China
[4] School of Communication and Culture, Aarhus University, Aarhus, Denmark
[5] Center for Humanities Computing, Aarhus University, Aarhus, Denmark

Abstract

The moods, feelings and attitudes represented in a novel will resonate in the reader by activating similar sentiments. It is generally accepted that sentiment analysis can capture aspects of such moods, feelings and attitudes and can be used to summarize a novel's plot in a story arc. With the availability of a number of algorithms to automatically extract sentiment-based story arcs, new approaches for their utilization becomes pertinent. We propose to use nonlinear adaptive filtering and fractal analysis in order to analyze the narrative coherence and dynamic evolution of a novel. Using *Never Let Me Go* by Kazuo Ishiguro, the winner of the 2017 Nobel Prize for Literature as an example, we show that: 1) nonlinear adaptive filtering extracts a story arc that reflects the tragic trend of the novel; 2) the story arc displays persistent dynamics as measured by the Hurst exponent at short and medium time scales; 3) the plots dynamic evolution is reflected in in the time-varying Hurst exponent. We argue that these findings are indicative of the potential multifractal theory has for computational narratology and large-scale literary analysis. Specifically, that the global Hurst exponent of a story arc is an index of narrative coherence that can identify bland, incoherent and coherent narratives on a continuous scale. And, further, that the local time-varying Hurst exponent captures variation of a novel's plot such that the extrema have specific narratological interpretations.

keywords: fractal analysis, Hurst exponent, sentiment analysis, story arcs, text analysis

1 Introduction

A novel that succeeds in capturing the joys and sorrows of human life will elicit a resonance of similar experiences in the reader either through memory (i.e., the reader's previous experiences) or imagination (i.e, the reader's imagined experiences). Readers will (re-)experience and share moods, feelings and attitudes, when reading a work of fiction, because the author has imbued the narrative with specific sentiments (sympathy, joy, irony, disgust, etc.) [1, 2]. How can we extract and quantify the narrative structure that is responsible for the reader's experience?

In affective computing, sentiment analysis encompasses a range of methods for detecting emotional features in texts. These methods predominantly classify sentiments at three levels: text [3, 4], phrase [5, 6], and sentence [7, 8]. Approaches to sentiments analysis are based either on a dictionary or machine learning - either

*Corresponding authors: Jianbo Gao, jbgao.pmb@aliyun.com; Kristoffer L. Nielbo, knielbo@sdu.dk

supervised or unsupervised [9, 10]. Because the current study is an application of a dictionary-based approach, machine learning will, regardless of its many interesting applications, not be discussed further. Dictionary-based sentiment analysis rely on lexical matching between a sentiment dictionary and a target data set. Dictionaries are typically generated manually or through a survey that assigns sentiment scores to words in a full-form word list. Criteria for word selection vary from expert-based to purely statistical [10]. While an advantages of dictionary-based approaches is their corpus independence, that is, they do not need training data, their use is not domain independent. Because the affective valence of a word can vary between text contexts, it can be necessary to construct domain-specific dictionaries. The polarity of "awful", for instance, is opposite in religious ("the awful majesty of God") and media ("Trump's awful Cabinet just got even worse") domains. The accuracy of dictionary-based approaches similarly suffers from text internal contextual errors, when, for instance, the polarity of words balance each other out ("I am not$_{negative}$ happy$_{positive}$"$_{NEUTRAL}$). In spite of this, dictionary-based sentiment analysis has gained tremendous popularity in for large-scale analysis of reviews [11], social media and microblogs [12], opinion mining [13] and short text analysis [14].

The majority of sentiment analyses ignore temporal and dynamic aspects of sentiment evolution in texts. Instead they estimate a central tendency of short texts (e.g., tweets or reviews), its positive/negative/neutral polarity, and extract a set of keywords for evaluation and opinion mining. Recently, there have been some developments in sentiment analysis of long literary texts [15, 16]. In these studies, sentiment dictionaries are used to extract a sentiment time series (a "story arc") that reflects a long text's narrative structure [17] [18]. Julian Brooke (2015) introduced an tool, GutenTag, which is aimed at giving literary scholars direct access this, and other NLP techniques, for analysis of texts in the Project Gutenberg corpus [19]. Another promising tool is Mathew Jockers' Syuzhet package for R [20]. This library is particularly interesting because it contains the Syuzhet lexicon, which is an English sentiment dictionary developed specifically for literary analysis. As important as the dictionary, is the question of how to extract a time series that reflect the narrative structure. Dodds (2015) used a custom dictionary to estimate the happiness time series of novels in windows of 10.000 words [21]. Jockers (2015) also used windowing with the Syuzhet dictionary combined with techniques from signal processing in order to compare story arcs [15]. Gao (2017) combined Syuzhet time series with nonlinear adaptive filtering to study the dynamic multi-level sentiment evolution of novels [22].

In this paper, we want to develop the application of multifractal theory to analysis of narrative structure (i.e., narratology). We are particularly interested in showing how nonlinear adaptive filtering and adaptive fractal analysis can be used to construct emotional story arcs, characterize the narrative coherence of a novel, and conduct fine-grained analysis of the narrative's dynamic evolution. For illustrative purpose, we analyze *Never Let Me Go* by the Nobel-prize winning British author Kazuo Ishiguro [23,24]. His authorship was praised by the Swedish Academy in its motivation for the award for having "uncovered the abyss beneath our illusory sense of connection with the world" and for being driven by a "great emotional force". The main plot of the novel is not complicated, but it contains multiple instances of suspense and foreshadowing, which, all things being equal, should motivate readers to continue reading for the revelation of characters' fates and the truth about the world described in the novel. Existing research mainly focuses on the novel's literary properties, e.g., its genre, theme and narrative technique [25], and the novel's social significance, e.g., relating to marginalized social groups [26] and human rights issues [25]. The rich and varied emotions expressed in the novel are generally ignored. From the perspective of sentiment analysis and literary studies, analyzing the dynamic evolution of *Never Let Me Go* is therefore tempting. The remainder of the paper is organized as follows: Section 2 introduces the methods of nonlinear adaptive filtering and adaptive fractal analysis. Section 3 and 4 extract the original and normalized sentiment story arcs and estimate their multifractal Hurst parameter. Section 5 analyzes the dynamic evolution of sentiment in *Never Let Me Go*. Section 6 summarizes the findings.

2 Methods

2.1 Nonlinear Adaptive Filtering

Sentiment story arcs are typically noisy and nonlinear [22]. It is therefore necessary with the method that can reduce noise and identify a global "narrative" trend in nonlinear time series. Because wavelet approaches are not ideal for detrending nonlinear series, Gao et al (2010) developed nonlinear adaptive filtering, which has been shown to be more effective than wavelet approaches for determining trends in nonlinear time series [27].

Nonlinear adaptive filtering [28] works as follows. First, we partition a time series into segments (or windows) of length $w = 2n+1$ points, where neighboring segments overlap by $n+1$. The time scale then is $n+1$ points, which ensures symmetry. Then, for each segment, we fit a polynomial of order D. Note that $D = 0$ means a piece-wise constant, and $D = 1$ a linear fit. The fitted polynomial for ith and $(i+1)th$ is denoted as $y^{(i)}(l_1), y^{(i+1)}(l_2)$, where $l_1, l_2 = 1, 2, ..., 2n+1$. Note the length of the last segment may be shorter than w. We use the following weights for the overlap of two segments.

$$y^{(c)}(l_1) = w_1 y^{(i)}(l+n) + w_2 y^{(i)}(l), l = 1, 2, ..., n+1$$

where $w_1 = (1 - \frac{l-1}{n}), w_2 = 1 - w_1$ can be written as $(1 - \frac{d_j}{n}), j = 1, 2$, where d_j denotes the distance between the point of overlapping segments and the center of $y^{(i)}, y^{(i+1)}$. This means that the weights decrease linearly with the distance between the point and the center of the segment. In fact, this treatment of the overlaps ensures that the filter is continuous everywhere, which ensures that non-boundary points are smooth.

2.2 Adaptive Fractal Analysis

Assuming that stochastic process $X = X_t : t = 0, 1, 2, ...$, with stable covariance, mean μ and σ^2, the process' autocorrelation function for $r(k), k \geq 0$ is:

$$r(k) = \frac{E\left[X(t)X(t+k)\right]}{E\left[X(t)^2\right]} \sim k^{2H-2}, as \quad k \to \infty$$

where H is called Hurst parameter [29]. For $0.5 < H < 1$ the process is characterized by long-range temporal correlations such that increments are followed by increases and decreases by further decreases. For $H = 0.5$ the time series only has short-range correlations also called short memory; and when $H < 0.5$ the time series is anti-persistent such that increments are followed by decreases and decreases by increments. In special cases $H > 1$, which characterizes a process that alternates between static behavior and bursts of chaotic behavior.

Detrended fluctuation analysis (DFA) is the most widely used method for estimating the Hurst parameter, but DFA may involve discontinuities at the boundaries of adjacent segments. Such discontinuities can be detrimental when the data contain trends [30], non-stationarity [31], or nonlinear oscillatory components [32, 33]. Adaptive fractal analysis (AFA) is a more robust alternative to DFA [34] [35] [36]. AFA consists of the following steps: first, the original process is transformed to a random walk process through first-order integration $u(n) = \sum_{k=1}^{n}(x(k) - \bar{x}), n = 1, 2, 3, ..., N$, where $\bar{x}$ is the mean of $x(k)$. Second, we extract the global trend $(v(i), i = 1, 2, 3, ..., N)$ through the nonlinear adaptive filtering. The residuals $(u(i) - v(i))$ reflect the fluctuations around a global trend. We obtain the Hurst parameter by estimating the slope of the linear fit between the residuals' standard deviation $F^{(2)}(w)$ and w window size as follows:

$$F^{(2)}(w) = \left[\frac{1}{N}\sum_{i=1}^{N}(u(i) - v(i))^2\right]^{\frac{1}{2}} \sim w^H$$

For classification of story arcs, we propose to interpret the Hurst exponent as follows: For persistent story arcs $0.5 < H < 1$, the novel has a coherent narrative, where the emotional intensity evolves at longer time scales. This creates meaningful and robust moods, feelings and attitude, and motivates the reader to continue reading the novel. Story arcs' that only show short memory, $H = 0.5$, lack narrative coherence and appear like a collection of short stories with only short-term correlations between emotional experiences. Anti-persistent story arcs, $H < 0.5$ display sentiment mean reversion, which will result in a bland and rigid narrative that oscillates fast around an average experience sentiment. Finally, for cases of $H > 1$, we expect the the narrative to be disruptive in the sense that coherent parts are interrupted by intensive emotional bursts. It is important to notice that the Hurst parameter of a story arc is not a direct measure of the arc's complexity. Novels that elicit incoherent reader experiences can be highly complex, while coherent novels can be almost completely predictable.

3 Global trend of original and normalized sentiment time series

The novel begins with the protagonist Kathy, a carer, recalling past events with her friends Ruth and Tommy (who became Cathy's lovers). They grew up together in the Hailsham boarding school and then parted afterwards. The title of the novel *Never Let Me Go* refers to Kathy's favorite music track on her most prized possessions, an album by Judy Bridgewater. The song later becomes a key prop in Tommy's confirmation of his love to Kathy. As a child, Kathy would sing "Never Let Me Go" while dancing with a pillow, not yet grasping its true meaning. When witnessing this scene, Madame (the real administrator of Hailsham) burst into tears, which represents an instance of suspense in the novel. The first instance of suspense is triggered when Miss Lucy, a teacher at Hailsham, says to the children that they are not being taught enough. Miss Lucy later leaves when the secret is revealed: the children are clones and bred to provide organs. The children are ignorant of their true destiny. There are several suspenseful moments in the novel, for instance when the children realize that the Madame is afraid of them; and when they describe that the Madame has a gallery, where has keeps their best work. Everything is finally revealed and the story ends, when Kathy stand in front of the ruined Hailsham and thinks about her dear lover Tommy, who was "completed" during his fourth organ donation, and her own doomed destiny: she will start her first donation within a month. Overall, Kathy's stoic attitude towards the use of the clones as spare parts for others, and the normality with which she describes this, would be stark contrast to the reader's perception of the fairness of this system and a source strong emotional engagement in the narrative.

In this paper, we extract sentiment time series using the Syuzhet sentiment dictionary [20]. Sentiment scores were extracted at sentence level from *Never Let Me Go* figure 1 (a1). For comparison, we length normalized sentiment scores by dividing each sentence score with its token length. Figure 1 (b1). The black curve in figure 1 is the raw sentiment time series in a1 and b1, which appear highly irregular. To filter noise and identify the story arcs, we applied nonlinear adaptive filtering (see Methods 2.1). Light gray curves are smoothed data at $w = 55$, dark gray smoothed at $w = 735$, and black curves in a2 and b2 at $w = 2763$. To enhance the story arcs after smoothing, a2 and b2 are scaled to $\{-1, 1\}$. Short and medium window sizes do however not reveal the novel's story arc, and we therefore suggest using large window sizes (black curves in Fig.1.a2 and b2).

The story arcs (black curves in figure 1 a2 and b2) show that the sentiment is negative in the beginning and end of the novel for the original and normalized data. We further observe a positive sentiment trend that peaks around the middle of the novel. The normalized story arc has a more pronounced secondary peak towards the end, a trend that is also present in the original data. The story arc clearly indicates that *Never Let Me Go* is a tragedy, where the ending is negative and below the arc's baseline. But a story arc can reveal more about the narrative structure than classification of literary genre. With an additional level of fractal analysis, it can be used to describe narrative coherence and dynamic evolution of sentiments.

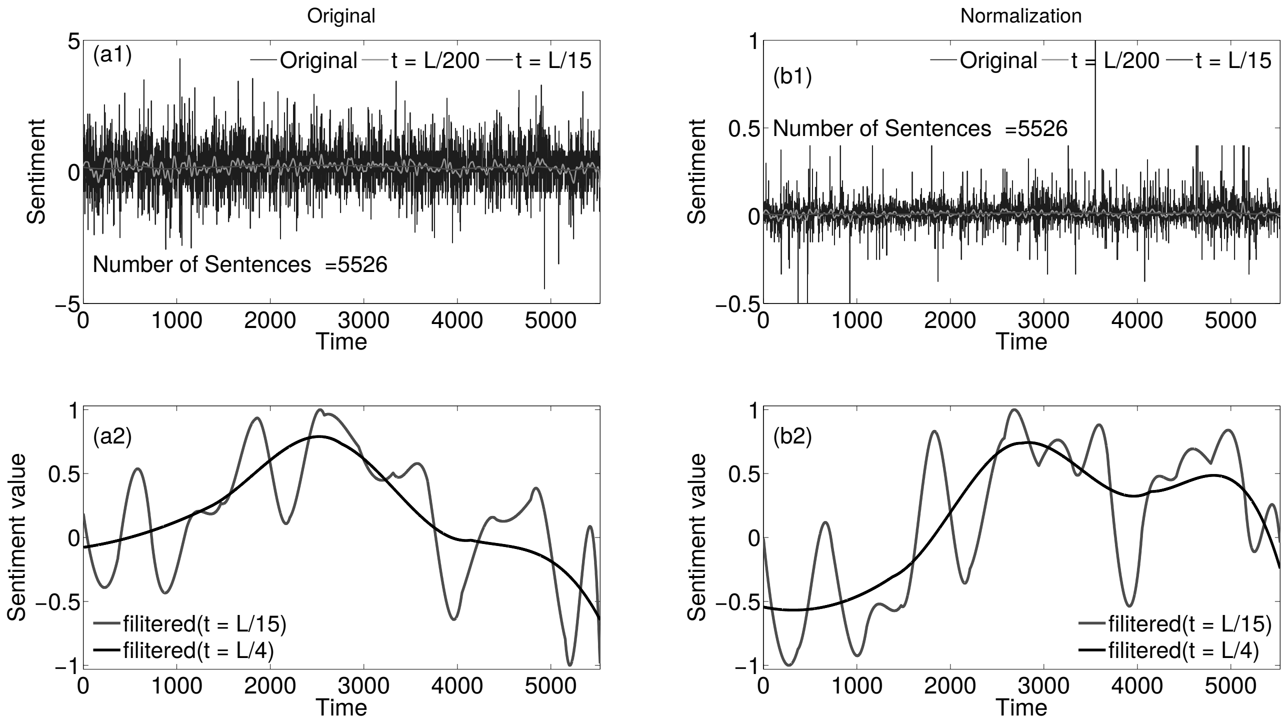

Figure 1: Sentiment time series and story arcs of *Never Let Me Go*

4 Hurst parameters of normalization and original sentiment value

We previously introduced the Hurst parameter H as an index of a novel's narrative coherence. To recapitulate H's interpretation for classification of story arcs, we propose that $0.5 < H < 1$ indicates long-range correlations in the sentiment time series. If H is close to the lower limit of $H = 0.5$, then the narrative has little coherence, but if it is close to the upper limit of $H = 1$ the narrative is almost too coherent or predictable. We speculate that optimal narrative coherence will be situated around the center of the range $\{0.5, 1\}$. In this paper we use AFA to estimate H. Figure 2 shows the H of *Never Let Me Go* for original (a) and normalized (b) sentiment time series. The novel is multifractal, as shown by the two sections of the linear fits and their corresponding Hs (H_s and H_l) in figure 2.

The linear fits are split in short ($w < 128$) and long ($w \geq 128$) time scales at 2^8 on the abscissa in figure 2. It is important to notice that at short time scales H_s is almost identical for the original and normalized sentiment time series. Our interpretation of $H \approx 0.61$ at short time scales is that a reader when reading less than 128 sentences, will experience the narrative as coherent with continuity in the experience of moods, feelings and attitudes. The reader will therefore be motivated to progress in their reading because the novel is neither incoherent nor overly predictable. At longer time scales the sentiment time series are anti-persistent since $H_l < 0.5$, although the difference between the original and normalized data is greater. This reflects mean reverting behavior of the sentiment time series, where negative emotions and balanced out by positive and vice verse in slices longer than 128 sentences. This could be an indication of a rigid narrative structure or, it could be argued, that the experiential unit of the novel is not long time scales. In the last case we would expect a different behavioral regime at long time scales. The decision between these options is fundamentally empirical and a task for large-scale literary analysis and reader psychology. To further illustrate the potential of multifractal theory in analysis of narrative structure, we turn to time-varying H in order to study the dynamic evolution of *Never Let Me Go*.

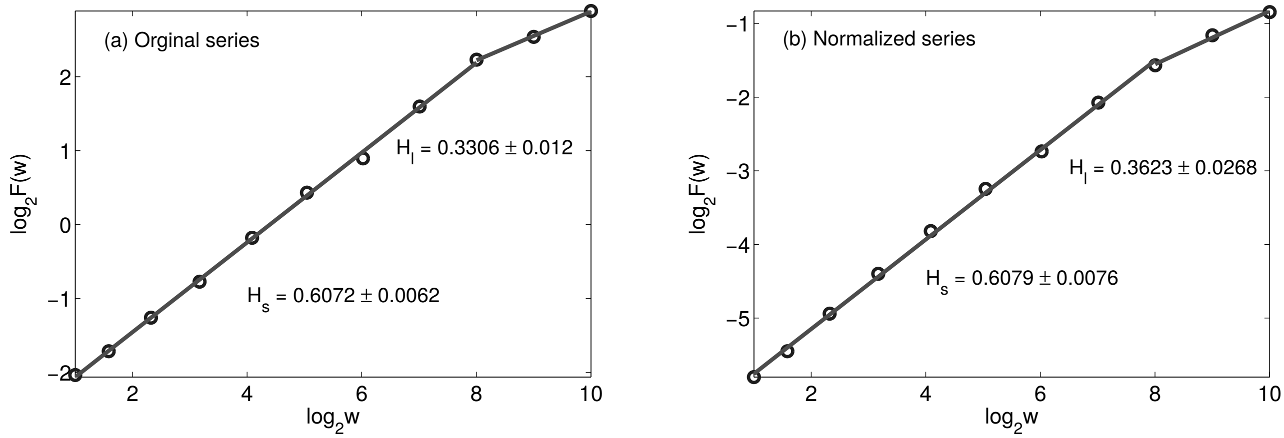

Figure 2: The Hurst parameters of original and normalization sentiment time series of *Never Let Me Go*

5 The dynamic evolution of sentiment in *Never Let Me Go*

Kazuo Ishiguro's novel is filled with emotional expressions. The upbringing of the clones is told with many details of how their emotional life is conditioned through education, friendships, and the creation of art. They shed tears and show empathy by wondering about the difference between themselves and the people whose lives they have been created to save. Kathy's role as a carer is from the beginning described as being able to manage emotions in the clones that are recovering from having parts of their body removed. To capture this detailed variation in the narrative's moods, feelings and attitudes, we estimate the Hurst parameter's for subsections of the novel, that is, we slide a moving window over the novel's sentiment time series and compute H for each window.

The appropriate window size was determined by minimizing residual errors in estimation of local Hs for multiple window sizes. This procedure were carried for the original and the normalized sentiment time series. For *Never Let Me Go* a window size of 256 sentences is appropriate. Figure 3 shows the time-varying H with $w = 256$; gray punctuated vertical lines separate chapters and black punctuated vertical lines split the novel into its three main parts. The three parts are most clearly observed in the normalized time series as local minima. Notice that the transition between part one and two is located at the global minimum. When important changes happen in the narrative, we see that the Hurst parameter goes down because the persistence of the sentiment time series is decreased. Transitions is in other words represented as random-like moments or disruptions.

To explain how the dynamic behavior of H reflects *Never Let Me Go*'s plot, we match the local minima with events in the novel (lower case letters in figure 3 (b)). At the beginning of the novel, Kathy gives a long description of the students and their campus life, which is reflected in the continuous increase of H. The first decline of H at point a represents an instance of suspense - when Kathy describes Miss Lucy telling the student that they were not being taught enough. Kathy then turns to the present and again the the past recalling events that occurred at Hailsham (local minimum at point b).

A new emotional state develops after b which culminates in c, one of the novel's most intriguing parts. In this part Miss Lucy talks to the students about their true destiny: they are clones, their fate is to provide organs to others. As a result Miss Lucy leaves Hailsham, which is reflected in a new local minimum c. After this, the novel expands on three aspects: 1) Miss Lucy leaving; 2) Ruth and Tommy's falling in love, breaking up and, finally, reconciling; and 3) campus life being finished. The three main characters (Kathy, Ruth, and Tommy) move to the Cottages, where the have contact the the outside world (at point d).

Point e represents the beginning of chapter 13. As H increases we observe three related events unfold: 1) a search for a Ruth's "possible", that is, the human she was cloned from; 2) a rumor that a couple can have

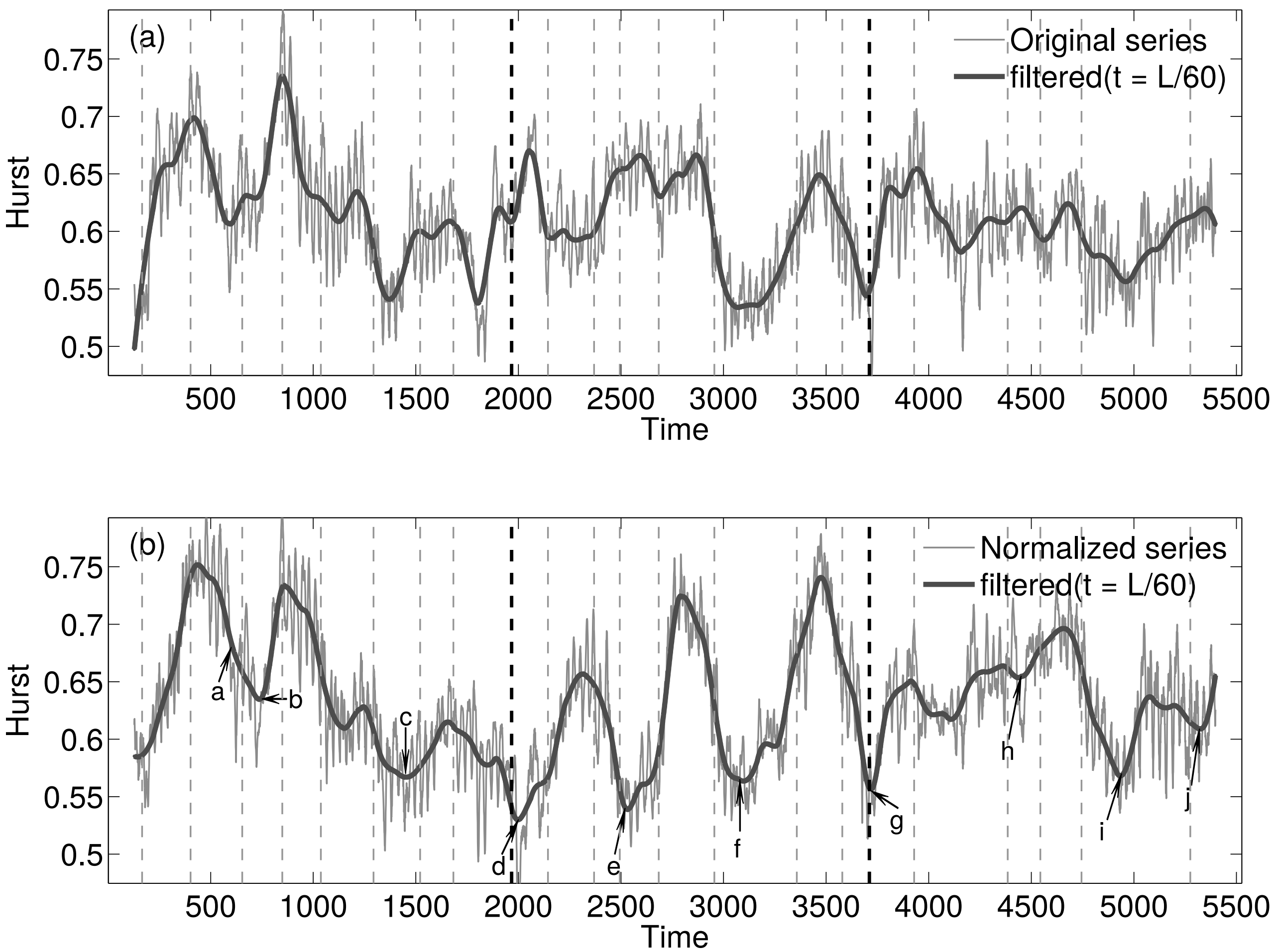

Figure 3: The evolution of Hurst under 256 window size of original and normalized sentiment time series

their donations deferred if they can prove their love; and 3) Ruth's "possible" is found, which makes Ruth wonder whether they are all cloned from "human trash". Again H evolves toward a local minimum at f, at which point Kathy and Tommy leave the others to search for a copy of the Judy Bridgewater tape that Kathy lost at Hailsham. Tommy's recollection of the tape and his desire to find it reflects the sincerity of his feelings for Kathy. The Kathy-Tommy relationship culminates in point g where Ruth destroy it resulting in Kathy's application to become a carer.

At point h Ruth expresses regret for keeping Kathy and Tommy apart, before she makes her second donation and completes (a euphemism for dying). After this H declines rapidly as Kathy becomes Tommy's carer and they engage in a romantic relationship. The decline reflects great change in the emotional content. Following this, in chapter 22, the plot thickens as Kathy and Tommy go to Madame's house to defer Tommy's fourth donation. The rumor that couples in true love can have their donations deferred turns out to be false, which is capture by H's local minimum at point i. In the last chapter of the novel, we see H rise continuously as Kathy is alone after Tommy's completion, knowing that she will start her first donation in a month.

6 Concluding remarks

Based on the illustrative application of nonlinear adaptive filtering and adaptive fractal analysis to *Never Let Me Go*'s sentiment time series, we would like to summarize with the following suggestions:

1. The (global) Hurst exponent of a novel's sentiment story arc provides an index of a novel's narrative coherence. This index can be used as an evaluation metric of how the novel's moods, feelings and attitudes will be perceived by a reader.
2. As an evaluation metric, the Hurst exponent of a novel can be interpreted accordingly: $0.5 < H < 1$ indicates a coherent narrative; $H = 0.5$ indicates a narrative that is incoherent, almost random (i.e., a collection of short stories); and $H < 0.5$ indicates a overly rigid and potentially bland narrative (i.e., a monotonous and predictable story).
3. the optimal narrative manages the reader's experience and motivation by neither being completely coherent ($H \approx 1$) nor incoherent ($H = 0.5$), but somewhere in between.
4. For $H > 0.5$, the (local) time-varying Hurst exponents reflects variation in the novel's plot, such that local minima reflect disruptions or points of narrative change, positive incline reflect continuous (persistent) narrative development, and decline a movement towards disruptions.

We expect that the application of multifractal theory to the analysis of story arcs will be valuable for three interrelated domains: computational narratology, large-scale literary analysis, and automated assessment of text quality. By iteself nonlinear adaptive filtering offers different levels of story arc abstraction [22], but in combination with fractal analysis it can be used to describe the coherence of a narrative with a summary metric H and capture the narrative's dynamic evolution. While story arcs based on sentiment dictionaries are already a valuable tool for computational narratology [16, 20], our approach offers a new way to evaluate and compare story arcs in terms of their narrative coherence. Is the narrative coherence of *Never Let Me Go* closer to the optimal narrative structure when compared to K. Ishiguro's other novels? And how does it compare to novels by other Nobel laureates in literature? Our approach also allows for cross language (e.g., Jesus Zulaika's Spanish translation *Nunca Me Abandones*) and media (e.g., Alex Garland's screenplay of *Never Let Me Go*) coherence analysis in order to compare how accurately different versions of the novel maintain the coherence of the original narrative.

It can be argued that our approach offers a new mid- (or "meso") level narrative analysis that bridges micro and macro-level reading for large-scale literary analysis. This argument is only partially true because it overlooks that our approach is more adequately described as multi-level. As a multi-level approach it combines micro-level analysis of sentence-by-sentence sentiment dynamics (i.e., local time-varying H exponents) with with mid-level work evaluation (i.e., H as a global index of narrative coherence) in a fully scalable framework (i.e., estimation of both local and global H can be fully automated). Future applications of our approach in large-scale literary analysis will be valuable both for the development of multifractal theory and narratology.

At the level of applied science, we believe that our approach can become a valuable tool for automated assessment of text quality. Estimation of a narrative's coherence can serve as a objective and continuous metric that can supplement the subjective score afforded by book review rating systems such as Likert-like scales measured in stars. Readers might even use H to identify their specific coherence preference. The publisher can use our approach to filter submitted manuscripts either manually by inspecting its H fits as in Fig. 2 or automatized by using the publishing house's back catalog and sales numbers to create a quality classifier based on H. Finally, an author can use the approach *in process* as a feedback technique for evaluating a manuscript at the level of local plot dynamics (i.e., time-varying H) and overall assessment (i.e., coherence index H).

References

[1] Hogan P C. Affective Narratology: The Emotional Structure of Stories, University of Nebraska Press, 2011.

[2] Bortolussi M, Dixon P. Psychonarratology: Foundations for the Empirical Study of Literary Response, Cambridge University Press, 2002.

[3] Turney P D. "Thumbs up or thumbs down?: semantic orientation applied to unsupervised classification of reviews", Proceedings of the 40th annual meeting on association for computational linguistics. Association for Computational Linguistics, 2002: 417-424.

[4] Pang B, Lee L. "A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts", Proceedings of the 42nd annual meeting on Association for Computational Linguistics. Association for Computational Linguistics, 2004: 271.

[5] Wilson T, Wiebe J, Hoffmann P. "Recognizing contextual polarity in phrase-level sentiment analysis", Proceedings of the conference on human language technology and empirical methods in natural language processing. Association for Computational Linguistics, 2005: 347-354.

[6] Agarwal A, Biadsy F, Mckeown K R. "Contextual phrase-level polarity analysis using lexical affect scoring and syntactic n-grams", Proceedings of the 12th Conference of the European Chapter of the Association for Computational Linguistics. Association for Computational Linguistics, 2009: 24-32.

[7] Hu M, Liu B. "Mining and summarizing customer reviews", Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, 2004: 168-177.

[8] Kim S M, Hovy E. "Determining the sentiment of opinions", Proceedings of the 20th international conference on Computational Linguistics. Association for Computational Linguistics, 2004: 1367.

[9] Medhat W, Hassan A, Korashy H. "Sentiment analysis algorithms and applications: A survey", Ain Shams Engineering Journal 4, 2014: 1093–1113.

[10] Reagan A, Tivnan B, Williams J R, Danforth C M, Dodds P S. "Benchmarking sentiment analysis methods for large-scale texts: A case for using continuum-scored words and word shift graphs", arXiv preprint arXiv:1512.00531, 2015.

[11] Mullen T, Collier N. "Sentiment analysis using support vector machines with diverse information sources", Proceedings of the 2004 conference on empirical methods in natural language processing. 2004.

[12] Nielsen F A. "A new ANEW: Evaluation of a word list for sentiment analysis in microblogs", arXiv preprint arXiv:1103.2903, 2011.

[13] Zhang L, Liu B. "Sentiment Analysis and Opinion Mining", Encyclopedia of Machine Learning and Data Mining, Springer, Boston, MA, 2017: 1152–1161.

[14] dos Santos C N, Gatti, M. "Deep Convolutional Neural Networks for Sentiment Analysis of Short Texts", Proceedings of COLING, 2014: 69–78.

[15] Jockers M. More Syuzhet Validation, 2016, [online] Available: http://www.matthewjockers.net/2016/08/11/more-syuzhet-validation/

[16] Reagan A J, Mitchell L, Kiley D, Danforth C M, Dodds P S. "The emotional arcs of stories are dominated by six basic shapes", arXiv preprint arXiv:1606.07772, 2016.

[17] E. Cambria, "Affective computing and sentiment analysis", IEEE Intelligent Systems, vol. 31, no. 2, pp. 102-107, 2016.

[18] E. Cambria, B. Schuller, Y.Q. Xia, C. Havasi, "New avenues in opinion mining and sentiment analysis", IEEE Intelligent Systems, March/April 2013.

[19] Julian Brooke et al. "GutenTag: An NLP-driven Tool for Digital Humanities Research in the Project Gutenberg Corpus", Proceedings of NAACL-HLT Fourth Workshop on Computational Linguistics for Literature.42-47,2015.1.4.

[20] Jockers M L. "Syuzhet: Extracts Sentiment and Sentiment-Derived Plot Arcs from Text", 2016, [online] Available: https://cran.r-project.org/web/packages/syuzhet/index.htm.

[21] Dodds P S, Clark E M, Desu S, Frank M, Reagan A J, Williams J R, Mitchell L, Harris K D, Kloumann I M, Bagrow J P. "Human language reveals a universal positivity bias", Proceedings of the National Academy of Sciences 112(8), 2016: 2389–2394.

[22] Gao J, Jockers M L, Laudun J, Tangherlini T. "A multiscale theory for the dynamical evolution of sentiment in novels". Behavioral, Economic and Socio-cultural Computing (BESC), 2016 International Conference on.

[23] Ishiguro, K. (2005). Never Let Me Go. London: Faber and Faber Limited.

[24] Thomsen M R. The New Human in Literature: Posthuman Visions of Changes in Body, Mind and Society after 1900, Bloomsbury Academic, 2015.

[25] Levy T. "Human Rights Storytelling and Trauma Narrative in Kazuo Ishiguro's Never Let Me Go", Journal of Human Rights 10, 2011: 1-16.

[26] Carroll R. "Imitations of life: cloning, heterosexuality and the human in Kazuo Ishiguro's Never let me go", Journal of Gender Studies 19(1), 2010: 59-71.

[27] Gao J B, Sult H, Hu J, Tung W W. "Denoising nonlinear time series by adaptive filtering and wavelet shrinkage: a comparison", IEEE Signal Processing Letters. 17, 2010: 237-240.

[28] Hu, J, Gao J B, Wang X S. "Multifractal analysis of sunspot time series: the effects of the 11-year cycle and Fourier truncation", J. Statistical Mech 2, 2009: P02066.

[29] Mandelbrot B B. The Fractal Geometry of Nature, San Francisco:Freeman, 1982.

[30] Hu K, Ivanov P Ch, Chen Z, Carpena P, Stanley H E. "Effect of trends on detrended fluctuation analysis", Physical Review E 64(1), 2001.

[31] Kantelhardt J W, Zschiegner S A, Koscielny-Bunde E, Havlin S, Bunde A, Stanley H E. Multifractal detrended fluctuation analysis of nonstationary time series, Physica A: Statistical Mechanics and its Applications 316(1-4), 2002: 87–114.

[32] Chen Z, Hu K, Carpena P, Bernaola-Galvan P, Stanley H E, Ivanov, P Ch. Effect of nonlinear filters on detrended fluctuation analysis, Phys. Rev. E 71(1), 2005: 011104.

[33] Hu J, Gao J, Wang X. Multifractal analysis of sunspot time series: the effects of the 11-year cycle and Fourier truncation, Journal of Statistical Mechanics: Theory and Experiment 2, 2009: P02066.

[34] Gao, J B, Hu J, Tung W W. "Facilitating joint chaos and fractal analysis of biosignals through nonlinear adaptive filtering", PLoS ONE 6, 2011.

[35] Tung W W, Gao J B, Hu J. "Detecting chaotic signals in heavy noise environments", Phys. Rev. E, 83, 2011.

[36] Gao J B, Cao Y H, Tung W W, Hu J. Multiscale Analysis of Complex Time Series, Integration of Chaos and Random Fractal Theory and Beyond, 2007.