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Linguistic Communication Channels Reveal Connections Between Texts: The New Testament and Greek Literature

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Abstract: We study two fundamental linguistic channels – the Sentences and the Interpunctions channels – and show they can reveal deeper connections between texts. The theory applied does not follow the actual paradigm of linguistic studies. As study–case, we consider the Greek New Testament, with the purpose of determining mathematical connections between its texts and possible differences in writing style (mathematically defined) of writers, and in reading skill required to their readers. The analysis is based on deep–language parameters and communication/information theory. To set the New Testament texts in the larger Greek Classical Literature, we consider texts written by Aesop, Polybius, Flavius Josephus and Plutarch. The results largely confirm what scholars have found about the New Testament texts giving, therefore, credibility to the theory. The gospel according to *John* is very similar to *Fables* written by Aesop. Surprisingly, the *Epistle to the Hebrews* and *Apocalypse*, are each other "photocopy" in the two linguistic channels, and not linked to all other texts. These two texts deserve further study by historians of the early Christian Church Literature at the level of meaning, readers and possible Old Testament texts which might have influenced them. The theory can guide scholars to study any literary corpus.

Keywords: Apocalypse; Deep–language; Greek New Testament; Greek Classical Literature; Epistle to the Hebrews; Interpunctions; Likeness index; Linguistic channels; Sentences; Signal–to–noise ratio; Vectors

1. A mathematical theory of texts outside the paradigm of natural language processing

In recent papers [1–8], we have developed a general theory on the deep–language mathematical structure of literary texts (or any long text), including their translation. The theory is based on linguistic communication channels – suitable defined– always contained in texts and based on the theory of regression lines [9, 10] and Shannon's communication and information theory [11].

In our theory, "translation" means not only the conversion of a text from a language to another language – what is properly understood as translation – but also how some linguistic parameters of a text are related to those of another text, either in the same language or in another language. "Translation", therefore, refers also to the case a text is mathematically compared (metaphorically "translated") to another text, whichever is the language of the two texts [2].

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The theory does not follow the actual paradigm of linguistic studies. Most studies on the relationships between texts concern translation because of the importance of automatic translation. References [12–18] report results not based on mathematical analysis of texts - as our theory does - and when a mathematical approach is used, as in References [19–51], most of these studies neither consider Shannon's communication theory, nor the fundamental connection that some linguistic variables seem to have with reading ability and STM capacity [1–8]. In fact, these studies are mainly concerned with automatic translations, not with a high–level direct response of human readers, as our theory does. Very often they refer only to one very limited linguistic variable, not to sentences which convey a completely developed thought – not to deep–language parameters, as our theory does.

The theory allows to perform experiments with ancient readers − otherwise impossible – or with modern readers, by studying the literary texts of their epoch. These "experiments" can reveal unexpected similarity and dependence between texts, because they consider mathematical parameters not consciously controlled by writers, either ancient or modern, as we will also show in the present paper.

Besides the total number of characters, words, sentences and interpunctions (punctuation marks) of a text, the linguistic parameters considered in our theory are: number of words n_W per chapter; number of sentences n_S per chapter; number of interpunctions per chapter n_I. Instead of referring to chapters, the analysis can refer to any chosen subdivision of a literary text, large enough to provide reliable statistics, such as few hundreds words [1-8].

We also consider four important deep–language parameters, calculated in each chapter (or in any large–enough block text): characters per word C_P; words per sentence P_F; words per interpunctions I_P; interpunctions per sentence $M_F = P_F/I_P$ (this variable gives the number of $I_P{}'s$ contained in a sentence).

The parameter I_P, also referred to as the "words interval" (i.e. an "interval" measured in words [1]) is very likely linked to readers' STM capacity [52] and it can be used to study how much two populations of readers of diverse languages overlap in reading a literary text in translation [7].

To study the chaotic data that emerge in any language, the theory compares a text (the reference, or input text) to another text (output text, "cross–channel") or to itself ("self–channel"), with a complex communication channel – made of several parallel single channels [4], two of which are explicitly considered in the present paper – in which both input and output are affected by "noise", i.e. by diverse scattering of the data around a mean linear relationship, namely a regression line.

In [3] we have shown how much the mathematical structure of a literary text is saved or lost in translation. To make objective comparisons, we have defined a likeness index I_L, based on probability and communication theory of noisy digital channels. We have shown that two linguistic parameters can be related by regression lines. This is a general feature of texts. If we consider the regression line linking n_S (dependent variable) to n_W (independent variable) in a reference text and the regression line linking the same parameters in another text, then n_S of the first text can be linked to n_S of the second text with another regression line without explicitly calculating its parameters (slope and correlation coefficient) from the samples, because the mathematical problem has the same structure of the theory developed in Reference [2].

In Reference [4] we have applied the theory of linguistic channels to show how an author shapes a character speaking to diverse audiences by diversifying and adjusting ("fine tuning") two important linguistic communication channels, namely the Sentences channel (S–channel) and the Interpunctions channel (I–channel). The S–channel links n_S of the output text to n_S of the input text, for the *same* number of words. The I–channel links M_F (i.e., the words intervals I_P) of the output text to M_F of the input text, for the the *same* number of sentences.

In Reference [5] we have further developed the theory of linguistic channels by applying it to Charles Dickens' novels and to other novels of the English Literature and found, for example, that this author was very likely affected by King James' New Testament.

In Reference [6] we have defined a universal readability index, applicable to any alphabetical language, by including readers' STM capacity, modelled by I_P; in Reference [7] we have studied the STM capacity across time and language and in Reference [8] the readability of a text across time and language.

In this paper, as the title claims, we further study linguistic communication channels – namely S–channels and I–channels – and show that they can reveal deeper connections between texts. As study–case, we consider an important historical literary corpus, the Greek New Testament (NT), with the purpose of determining mathematical connections between its books (in the following referred to as "texts"), and possible differences in writing style (mathematically defined) of writers and in reading skill required to their readers. To set the NT texts in the Greek Classical Literature, we have considered texts written by Aesop, Polybius, Flavius Josephus and Plutarch.

The analysis is based on the deep–language parameters and communication channels mentioned above, not explicitly known to the ancient writer/reader or, as well, to any modern writer/reader not acquainted with this theory.

After this introductory section, Section 2 recalls and defines the deep–language parameters of texts; Section 3 recalls the vector representation of texts; Section 4 summarizes the theory of linguistic communication channels; Section 5 defines the theoretical signal–to–noise ratio in linguistic channels (S–channels and I–channels); Section 6 defines the experimental signal–to–noise ratio in these channels; Section 7 recalls the likeness index of texts and defines the channels quadrants; Section 8 presents an extreme synthesis of the main findings and Section 9 concludes and suggests future work. Appendices A and B reports numerical tables.

2. Deep–language parameters of texts

The original NT Greek texts were first processed manually to delete all notes, titles and other textual material added by modern editors, therefore leaving in the end only the original texts, as it was done in Reference [53].

Interpunctions were introduced by ancient readers acting as "editors" [54]. They were well–educated readers of the early Christian Church, very respectful of the original text and its meaning, therefore they likely maintained a correct subdivision in sentences and words intervals within sentences, for not distorting the correct meaning and emphasis of the text. In other terms, we can reasonably assume that interpunctions were effectively introduced by the author.

In Reference [53], we have compared the gospels according to *Matthew* (Mt), *Mark* (Mk), *Luke* (Lk), *John* (Jh) and the book of *Acts* (Ac) by considering only deep–language parameters, not S–channels and I–channels, as we do in this paper. Moreover, we have presently enlarged our study–case by including the *Epistle to the Hebrews* (Hb) and *Apocalypse* (Ap, known also as *Revelation*) – texts which show unexpected connections – and some texts written by the historians Polybius (Po), Plutarch (Pl), Flavius Josephus (Fl) and by the story–teller Aesop (Ae) to set the NT in the larger classical Greek Literature.

The samples used in the statistical analysis refer to chapters: for example, *Matthew* has 28 chapters, therefore this text is described by 28 samples for each deep–language parameter. The list of names ("genealogy" of Jesus of Nazareth) in *Matthew* and in *Luke* have been deleted for not biasing the statistical results. Like in References [1,2,3,4,5,6,7,8,13], samples were statistically weighted with the fraction of total words, therefore in *Matthew* – which contains 18121 total words – Chapter 5, for example, has 824 words, therefore its weight is $824/18121 = 0.0455$, not $1/128 = 0.0078$. This choice is mandatory to avoid that a short chapter (or, in general, a short text) affects the statistical results like a long one.

After this processing we have obtained the mean values of C_P, P_F, I_P, M_F reported in Table 1, and the universal readability G_U, defined and discussed in Reference [6], here calculated with the mean values $< P_F >$ and $< I_P >$ from:

$$G_U = 89 - 10 < C_P > + \frac{300}{< P_F >} - 6 \times (< I_P > - 6) \qquad (1)$$

In Equation (1) we set $< C_P > = 4.48$, the mean value found in the Italian Literature, since Italian is the reference language in the definition of G_U [1].

Table 1: New Testament. Mean values (averaged over all chapters) of C_P (characters per word), P_F (words per sentence), M_F (interpunctions per sentence), I_P (words per interpunctions) and G_U (universal readability index). The genealogy in Matthew (verses 1.1–1.17) and in Luke (verses 3.23–3.38) have been deleted for not biasing the statistical analyses. All parameters have been computed by weighting a chapter with the fraction of total words of the literary text.

Book	Total Words	$< C_P >$	$< P_F >$	$< M_F >$	$< I_P >$	G_U
Matthew	18,121	4.91	20.27	2.83	7.18	53.90
Mark	11,393	4.96	19.14	2.68	7.17	54.87
Luke	19,384	4.91	20.47	2.89	7.11	54.21
John	15,503	4.54	18.56	2.74	6.79	57.65
Acts	18,757	5.10	25.47	2.91	8.77	41.37
Hebrews	4,940	5.33	32.00	4.53	7.02	53.10

Apocalypse	9,870	4.66	30.70	3.97	7.79	49.46

To set the NT texts in the Greek Classical Literature, we have considered texts written by Aesop, Polybius, Flavius Josephus and Plutarch. The rational for selecting these authors is the following: Aesop wrote texts (*Fables*) which may recall the parables of the gospels for their brevity and similar narrative style; Polybius, Flavius Josephus and Plutarch were historians, therefore wrote essays narrating facts, like the gospels, partially, and especially *Acts*. Table 2 lists texts and mean values of the deep–language parameters of these authors. These texts have been processed manually like the NT.

Table 2. Greek Literature. Mean values (averaged over all chapters) of C_P (characters per word), P_F (words per sentence), M_F (interpunctions per sentence), I_P (words per interpunctions, or words interval) and the corresponding G_U (universal readability index). All parameters have been computed by weighting a chapter with the fraction of total words of the literary text.

Author	**Total Words**	$< C_P >$	$< P_F >$	$< M_F >$	$< I_P >$	G_U
Aesop (620–564 BC, *Fables*)	39,122	5.24	18.29	3.46	5.28	64.95
Polybius (200–118 BC, *The Histories*)	256,495	5.97	29.19	3.30	8.88	37.22
Flavius Josephus (37–100 AD, *The Jewish War*)	121,717	5.51	31.05	3.20	9.74	31.44
Plutarch (46–119 AD, *Parallel Lives*)	499,683	5.51	29.35	3.73	7.82	43.53

The mean values of Tables 1 and 2 can be used for a first assessment of how "close", or mathematically similar, texts are in a Cartesian plane, by defining a linear combination of deep–language parameters. Texts are then modelled as vectors, representation discussed in detail in [1-6] and briefly recalled in the next section.

3. Vector representation of texts

Let us consider the following six vectors of the indicated components of deep–language parameter: $\overrightarrow{R_1} = (< C_P >, < P_F >)$, $\overrightarrow{R_2} = (< M_F >, < P_F >)$, $\overrightarrow{R_3} = (< I_P >, < P_F >)$, $\overrightarrow{R_4} = (< C_P >, < M_F >)$, $\overrightarrow{R_5} = (< I_P >, < M_F >)$, $\overrightarrow{R_6} = (< I_P >, < C_P >)$ and their resulting sum:

$$\vec{R} = \sum_{k=1}^{6} \overrightarrow{R_k} \qquad (2)$$

By considering the coordinates x and y of Equation (2), we obtain the scatterplot of their ending points shown in Figure 1 where the coordinates X and Y are normalized so that Aesop's *Fables* (Ae) is at the origin $(X = 0, Y = 0)$ and Flavius Josephus' *The Jewish War* (Fl) is at $(X = 1, Y = 1)$.

In this Cartesian plane two texts are likely connected – they show close ending points – if their relative Pythagorean distance is small, and are likely not connected if their distance is large. In other words, a small distance means that texts share a similar mathematical structure. This is a necessary, but not sufficient, condition for two texts being each other very likely connected.

In Figure 1, the three synoptic gospels (Mt, Mk, Lk) are the closest texts of the NT. In particular, Mt and Lk are practically coincident, almost a mathematical "photocopy" of each other, as it was also shown, with diverse analysis, in Reference [1,2]. Notice also that

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G_U (Table 1) is very similar for the Synoptics but not for the other NT texts (except *Hebrews*), and that *John* (Jh) is the most readable text.

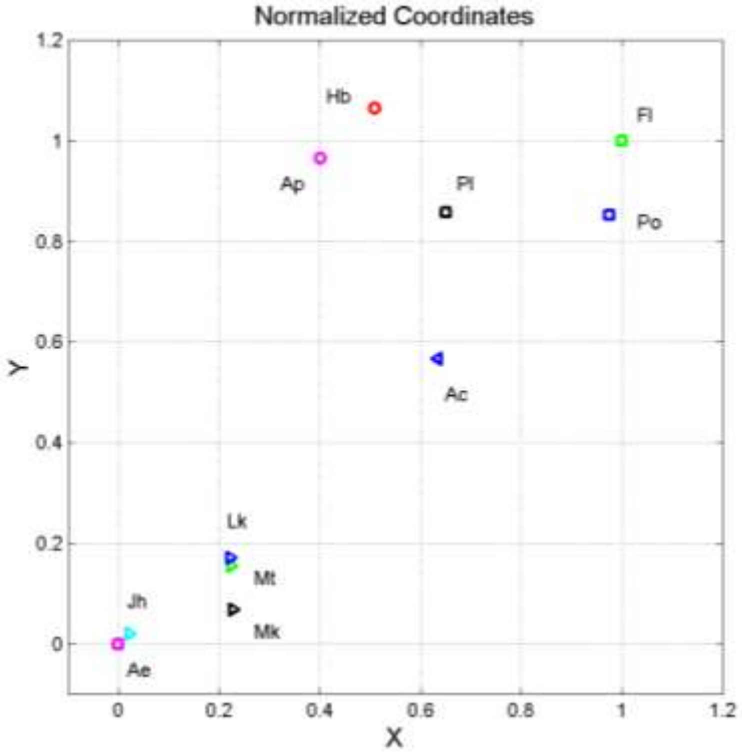

Figure 1. Normalized coordinates X and Y of the ending point of vector (5) such that *Aesop* (0,0) (Ae, magenta square) and *Flavius Josephus* (1,1) (Fl, green square). *Matthew* (Mt, green triangle); *Mark* (Mk, black triangle); *Luke* (Lk, blue triangle oriented to the right); *John* (Jh, cyan triangle); *Acts* (Ac, blue triangle oriented to the left); *Flavius Josephus* (Fl, green square); *Hebrews* (Hb, red circle); *Apocalypse* (Ap, magenta circle); *Polybius* (Po, blue square); *Plutarch* (Pl, black square).

Acts and *Luke*, although written by the same author – as widely accepted by scholars in References [55,60], a very small selection of the huge literature on this topic – are quite diverse because when Luke writes the gospel he has significant constraints because his sources are very likely shared with Matthew. But when Luke writes *Acts,* he has few or no sources to share with Matthew, therefore he is free to use his personal writing style oriented to narrating the early facts of the Church. It is not surprising, therefore, that *Acts*, because of its contents, is closer to Plutarch and Polybius than to the synpotics and that its $G_U = 41.37$ is close to Plutarchs' *Parallel Lives* $G_U = 45.53$ (Tables 1,2), therefore shading some light on the similar readability skill required to the readers of these historical narrations, and the gospels for which G_U ranges form 53.90 to 57.65.

John is distinctly diverse of *Matthew*, *Luke* and *Mark*, but it is very close to Aesop's *Fables*.

Unexpected is the vicinity of *Hebrews* and *Apocalyse* – two NT texts scholars rarely consider to be connected [60-63] – and their great distance from the gospels. Their universal readability indices are also very similar, $G_U = 53.10$ for *Hebrews* and $G_U = 49.46$ for *Apocalypse*.

As for the Greek historians, we can notice that they are distinctly grouped and distant from the gospels.

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In conclusion, the vector modelling of texts can reveal first connections, otherwise hidden. These connections can be further addressed by studying their S–channels and I–channels, and the likeness index I_L. Therefore, in the next section we first recall the theory of linguistic communication channels.

4. Theory of linguistic communication channels

In a text an independent (reference) variable x (e.g. n_W in S–channels) and a dependent variable y (e.g., n_S) can be related by a regression line (slope m) passing through the origin of the Cartesian coordinates:

$$y = mx \qquad (3)$$

Let us consider two diverse texts Y_k and Y_j. For both we can write Equation (3) for the same couple of parameters, however, in both cases Equation (3) does not give the full relationship of two parameters because it links only mean conditional values. We can write more general linear relationships which take care of the scattering of the data – measured by the correlation coefficients r_k and r_j, respectively, not considered in Equation (3) – around the regression lines (slopes m_k and m_j):

$$\boldsymbol{y_k} = \boldsymbol{m_k x} + \boldsymbol{n_k} \qquad (4)$$

$$\boldsymbol{y_j} = \boldsymbol{m_j x} + \boldsymbol{n_j}$$

While Equation (3) connects the dependent variable y to the independent variable x only on the average, Equation (4) introduces additive "noise" n_k and n_j, with zero mean value [2–4]. The noise is due to the correlation coefficient $|r| \neq 1$, not considered by Equation (1).

We can compare two texts by eliminating x. In other words, we compare the output variable y for the same value of the input variable x in the two texts. In the example just mentioned, we can compare the number of sentences in two texts – for an equal number of words – by considering not only the mean relationship, Equation (3), but also the scattering of the data, Equation (4).

As recalled before, we refer to this communication channel as the "sentences channel" and to this processing as "fine tuning" because it deepens the analysis of the data and provides more insight into the relationship between two texts. The mathematical theory follows.

By eliminating x, from Equation (4) we get the linear relationship between – now – the of sentences in text Y_k (now the reference, input text) and the sentences in text Y_j (now the output text):

$$\boldsymbol{y_j} = \frac{m_j}{m_k}\boldsymbol{y_k} - \frac{m_j}{m_k}\boldsymbol{n_k} + \boldsymbol{n_j} \qquad (5)$$

Compared to the independent (input) text $\boldsymbol{Y_k}$, the slope $\boldsymbol{m_{jk}}$ is given by:

$$\boldsymbol{m_{jk}} = \frac{m_j}{m_k} \qquad (6)$$

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The noise source that produces the correlation coefficient between $\boldsymbol{Y_k}$ and $\boldsymbol{Y_j}$ is given by:

$$\boldsymbol{n_{jk}} = -\frac{\boldsymbol{m_j}}{\boldsymbol{m_k}}\boldsymbol{n_k} + \boldsymbol{n_j} = -\boldsymbol{m_{jk}}\boldsymbol{n_k} + \boldsymbol{n_j} \qquad (7)$$

The "regression noise–to–signal ratio", $\boldsymbol{R_m}$, due to $|\boldsymbol{m_{jk}}| \neq \boldsymbol{1}$, of the channel is given by [2]:

$$\boldsymbol{R_m} = (\boldsymbol{m_{jk}} - \boldsymbol{1})^{\boldsymbol{2}} \qquad (8)$$

The unknown correlation coefficient $\boldsymbol{r_{jk}}$ between $\boldsymbol{y_j}$ and $\boldsymbol{y_k}$ is given by [2, 9]:

$$\boldsymbol{r_{jk}} = \mathbf{cos}|\mathbf{arcos}(\boldsymbol{r_j}) - \mathbf{arcos}(\boldsymbol{r_k})| \qquad (9)$$

The "correlation noise–to–signal ratio", $\boldsymbol{R_r}$, due to $|\boldsymbol{r_{jk}}| < \boldsymbol{1}$, of the channel that connects the input text $\boldsymbol{Y_k}$ to the output text $\boldsymbol{Y_j}$ is given by [1]:

$$\boldsymbol{R_r} = \frac{\boldsymbol{1-r_{jk}^2}}{\boldsymbol{r_{jk}^2}}\boldsymbol{m_{jk}^2} \qquad (10)$$

Because the two noise sources are disjoint and additive, the total noise–to–signal ratio of the channel connecting text $\boldsymbol{Y_k}$ to text $\boldsymbol{Y_j}$ is given by [2]:

$$\boldsymbol{R} = (\boldsymbol{m_{jk}} - \boldsymbol{1})^{\boldsymbol{2}} + \frac{\boldsymbol{1-r_{jk}^2}}{\boldsymbol{r_{jk}^2}}\boldsymbol{m_{jk}^2} \qquad (11)$$

Notice that Equation (9) can be represented graphically [2], to study the impact of R_m and R_R on R. Finally, the total signal–to–noise ratio is given by:

$$\gamma_{th} = 1/R \qquad (12)$$

$$\Gamma_{th} = 10 \times \log_{10}\gamma_{th} \qquad \text{(dB)}$$

Notice that no channel can yield $|r_{jk}| = 1$ and $|m_{jk}| = 1$ (i.e., $\Gamma_{th} = \infty$) a case referred to as the ideal channel, unless a text is compared with itself (self–comparison, self–channel). In practice, we always find $|r_{jk}| < 1$ and $|m_{jk}| \neq 1$. The slope m_{jk} measures the multiplicative "bias" of the dependent variable compared to the independent variable; the correlation coefficient r_{jk} measures how "precise" the linear best fit is.

In conclusion, the slope m_{jk} is the source of the regression noise, the correlation coefficient r_{jk} is the source of the correlation noise of the channel.

In the next section we study how sentences and interpunctions build S–channels and I–channels, and calculate their theoretical signal–to–noise ratio.

5. S–channels and I–channels: Theoretical signal–to–noise ratio $\boldsymbol{\Gamma_{th}}$

In S–channels the number of sentences of two texts is compared for the same number of words. Therefore, they describe how many sentences the writer of text j uses to convey a meaning, compared to the writer of text k – who may convey, of course, a diverse meaning – by using the *same* number of words. Simply stated, it is all about how a writer shapes his/her style in communicating the full meaning of a sentence with a given number of words available, therefore it is more linked to P_F than to other parameters.

In I–channels the number of words intervals I_P of two texts is compared for the *same* number of sentences. Therefore, they describe how many short texts (the text between two contiguous punctuation marks) two writers use to make a full sentence. Since I_P is very likely connected with short–term memory [1], I–channels are more related to readers' STM capacity than to authors' style.

Finally, notice the the universal readability index, Equation (1), depends on both P_F and I_P, therefore it can better measure reading difficulty, as discussed in Reference [6].

To apply the theory of Section 4, we need the slope m and the correlation coefficient r of the regression line between: (a) n_S and n_W to study S–channels; (b) n_I and n_S to study I–channels. We first consider the NT and then the texts from the Greek Literature.

5.1. New Testament

Table 3 reports the slope m and the correlation coefficient r of the regression line in the NT texts. In *Matthew*, for example, if we set $n_W = 100$ words then the text, on the average, contains $n_S = 100 \times 0.0508 = 5.08$ sentences and $2.7271 \times 5.08 = 13.85$ interpunctions.

Figures 2 and 3 show the scatterplots and regression lines linking n_S to n_W, and Figures 4 and 5 show those linking n_I to n_S. By looking at these figures, we can see at glance which texts have very similar regression lines, but it is more difficult to see whether the scattering of data is similar or not.

Table 3. Slope m and the correlation coefficient r of the regression lines of n_S versus n_W, and n_I versus n_S in the indicated texts. Four decimal digits are reported because some values differ only from the third digit. These parameters are calculated by uniformly weighing each block text, e.g. weight $1/28$ in *Matthew*.

Text	n_S versus n_W		n_I versus n_S	
	m	r	m	r
Matthew	0.0508	0.9410	2.7271	0.9548
Mark	0.0538	0.8985	2.5527	0.8800
Luke	0.0499	0.8975	2.8296	0.9243
John	0.0549	0.9181	2.6797	0.9517
Acts	0.0413	0.8807	2.7192	0.9280
Hebrews	0.0336	0.8037	4.0970	0.9005
Apocalypse	0.0338	0.8063	3.7605	0.8173

Regression lines, however, consider and describe only one aspect of the linear relationship, namely that concerning (conditional) mean values. They do not consider the other aspect of the relationship, namely the scattering of data, which may not be similar when two regression lines almost coincide, as it is clearly shown in Figure 2 in *Mark* and *John*, in *Matthew* and *Luke* and in *Hebrews* and *Apocalypse*. The theory of linguistic channels (Section 4), on the contrary, by considering both slopes and correlation coefficients, provides a reliable tool to fully compare two sets of data and can confirm the findings shown in Figure 1.

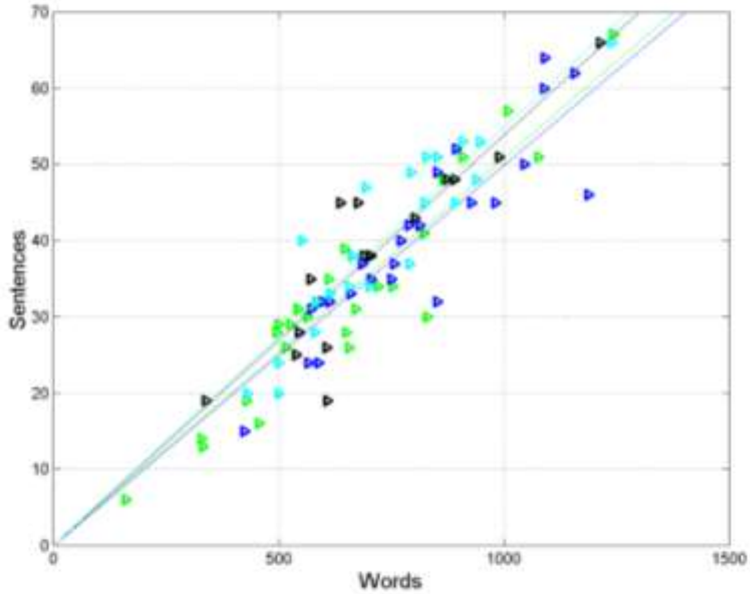

Figure 2. Scatterplots and regression lines between n_W (words, independent variable) and n_S (sentences, dependent variable) in the following texts: *Matthew* (green triangles and green line); *Mark* (black triangles and black line); *Luke* (blue triangles and blue line); *John* (cyan triangles and cyan line).

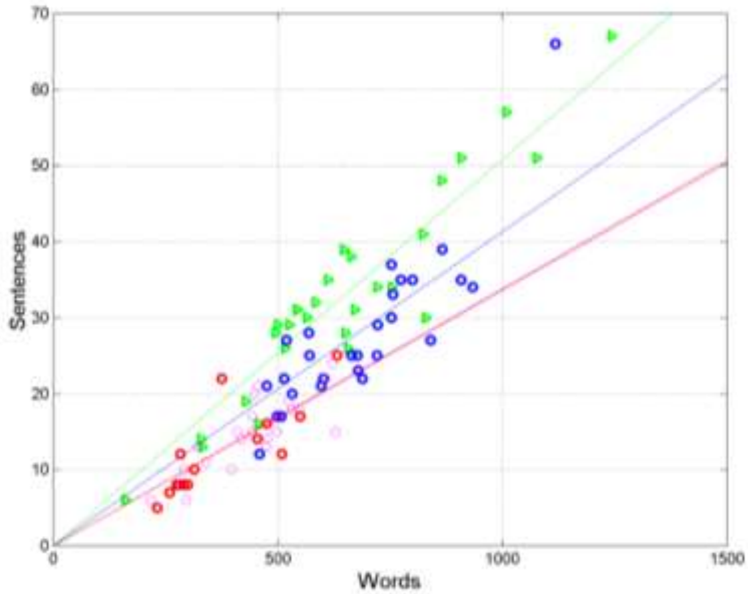

Figure 3. Scatterplots and regression lines between n_W (words, independent variable) and n_S (sentences, dependent variable) in the following texts: *Matthew* (green triangles and green line); *Acts* (blue circles and blue line); *Hebrews* (red circles and red line); *Apocalypse* (magenta circles and magenta line). The magenta line (*Apocalypse*) and the red line (*Hebrews*) are superposed because they practically coincide (see Table 3).

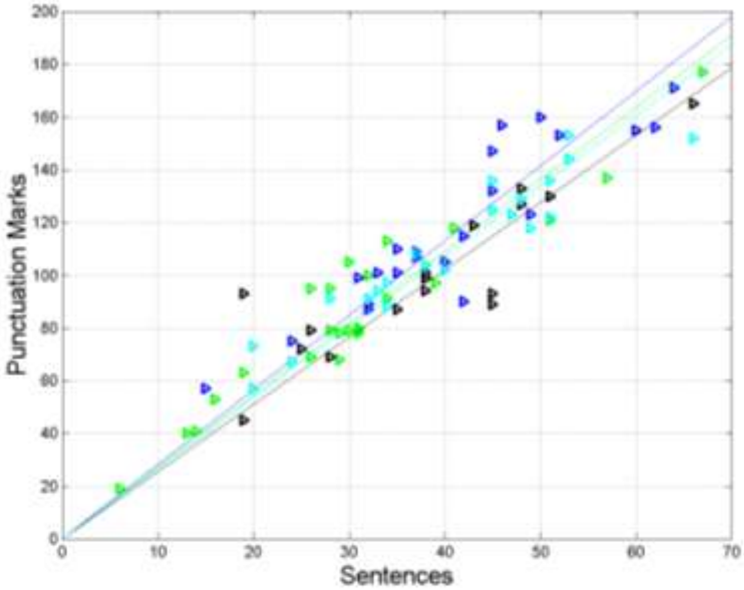

Figure 4. Scatterplots and regression lines between n_S (sentences, independent variable) and n_I (interpunctions, dependent variable) in the following texts: *Matthew* (green triangles and green line); *Mark* (black triangles and black line); *Luke* (blue triangles and blue line); *John* (cyan triangles and cyan line).

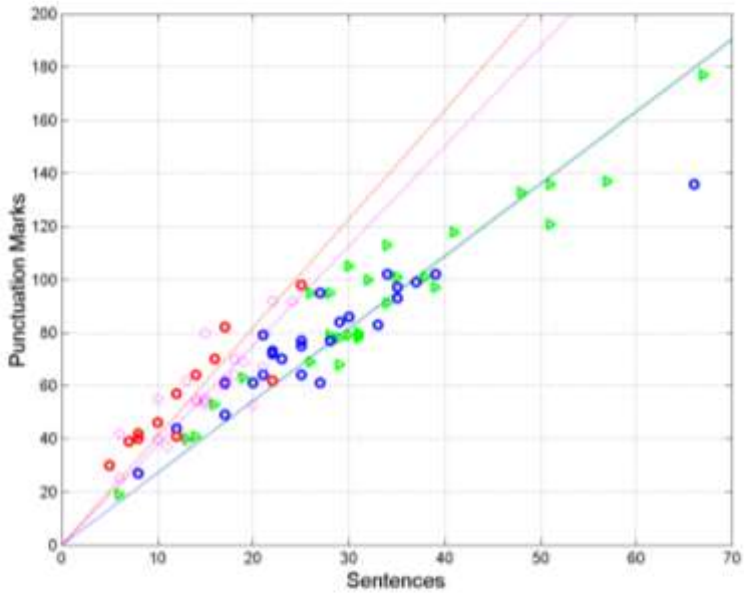

Figure 5. Scatterplots and regression lines between n_S (sentences, independent variable) and n_I (interpunctions, dependent variable) in the following texts: *Matthew* (green triangles and green line); *Acts* (blue circles and blue line); *Hebrews* (red circles and red line); *Apocalypse* (magenta circles and magenta line). The green line (*Matthew*) and the blue line (*Acts*) are superposed because they practically coincide (see Table 3).

As an example, Table 4 reports the calculated values of m_{jk} – Equation (6)– and r_{jk} – Equation (9) – in S–channels and in I–channels by assuming *Matthew* as the output text and the others as input texts. For instance, the number of sentences in *Matthew* (text Y_j) is linked to the sentences in *Luke* (text Y_k) – for the same number of words – with a regression line with slope $m_{jk} = 1.0180$ and correlation coefficient $r_{jk} = 0.9938$. In other terms, 100 sentences in *Luke* give $1.0180 \times 100 = 101.80$ sentences in *Matthew*, for the same

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number of words. The number of interpunctions in *Matthew* (text Y_j) is linked to the interpunctions in *Luke* (text Y_k) – for the same number of sentences – with a regression line with $m_{jk} = 0.9638$ and $r_{jk} = 0.9960$.

Table 4. Theoretical slope and correlation coefficient of the regression line according to Section 4, for the indicated input texts. Output Channel: *Matthew*.

Text	Sentences versus Sentences		Interpunctions versus Interpunctions	
	m_{jk}	r_{jk}	m_{jk}	r_{jk}
Mark	0.9442	0.9940	1.0683	0.9814
Luke	1.0180	0.9938	0.9638	0.9960
John	0.9253	0.9981	1.0177	0.9999
Acts	1.2300	0.9890	1.0029	0.9968
Hebrews	1.5119	0.9576	0.6656	0.9891
Apocalypse	1.5030	0.9589	0.7252	0.9516

Let us calculate the theoretical signal–to–noise ratio Γ_{th} obtained in S–channels and in I–channels. Table 5 (S–channel) and Table 6 (I–channel) report Γ_{th} between the input text indicated in the first column and the output text indicated in the first line.

Let us examine in detail some results.

In S–channels (Table 5), if the input is *Matthew* (first column) and the output is *Luke* (fourth column, channel *Matthew→Luke*) then $\Gamma_{th} = 19.06$; vice versa, if the input is *Luke* and the output is *Matthew* (*Luke→Matthew*) then $\Gamma_{th} = 18.76$, typical asymmetry present in literary texts [2-5].

In I–channels (Table 6), we read $\Gamma_{th} = 19.94$ in *Matthew→Luke* and $\Gamma_{th} = 20.53$ in *Luke→Matthew*. These results say that not only the asymmetry is very small, but, more important, that the S–channel and the I–channel are practically identical, with a $\Gamma_{th} \approx 19{\sim}20$, therefore confirming that the very small distance between *Matthew* and *Luke* shown in Figure 1 is not due to chance. From the point of view of communication theory, therefore, *Matthew* and *Luke* appear as each other mathematical "photocopy".

Table 5. S–channel. Theoretical signal–to–noise ratio Γ_{th} (dB) in the channel between the (input) text indicated in the first column and the (output) text indicated in the first line. For example, if the input is *Matthew* and the output is *Mark*, then $\Gamma_{th} = 17.70$; vice versa if the input is *Mark* and the output is *Matthew*, then $\Gamma_{th} = 18.59$.

Text	Matthew	Mark	Luke	John	Acts	Hebrews	Apocalypse
Matthew	∞	17.70	19.06	19.56	13.04	8.12	8.22
Mark	18.59	∞	22.79	25.66	12.61	8.12	8.21
Luke	18.76	22.14	∞	18.87	15.14	9.14	9.26
John	20.50	25.99	19.87	∞	11.83	7.67	7.76
Acts	10.62	10.26	13.44	9.15	∞	13.13	13.36
Hebrews	3.29	3.48	5.10	2.61	10.75	∞	42.61
Apocalypse	3.46	3.64	5.29	2.77	11.04	42.68	∞

Table 6. I–channel. Theoretical signal–to–noise ratio $\Gamma_{th,dB}$ (dB) in the channel between the (input) text indicated in the first column and the (output) text indicated in the first line. For example, if the input is *Matthew* and the output is *Mark*, then $\Gamma_{th}=14.25$, vice versa if the input is *Mark* and the output is *Matthew*, then $\Gamma_{th}=13.16$.

Text	Matthew	Mark	Luke	John	Acts	Hebrews	Apocalypse
Matthew	∞	14.25	19.94	33.94	21.94	5.19	4.66
Mark	13.16	∞	16.02	13.96	17.23	4.30	5.94
Luke	20.53	17.37	∞	20.70	27.93	6.82	7.02
John	33.75	14.78	19.91	∞	22.81	4.89	4.51
Acts	21.89	18.20	27.56	23.06	∞	5.73	5.96
Hebrews	9.15	8.45	10.12	8.93	9.39	∞	15.25
Apocalypse	8.85	9.60	10.45	8.80	9.75	13.92	∞

Luke and *Acts*, both universally attributed to Luke [55-65], have very similar Γ_{th} in the S–channel: $\Gamma_{th}=15.14$ in *Luke*→*Acts* and $\Gamma_{th}=13.44$ in $Acts \rightarrow Luke$. These values are low enough to agree with the large distance shown in Figure 1, therefore the style used in the two texts is significantly diverse, in agreement with the diverse values $<P_F>=20.47$ in *Luke* and $<P_F>=25.47$ in *Acts*. On the contrary, the large and practically identical values in the I–channel – $\Gamma_{th}=27.93$ in *Luke*→*Acts* and $\Gamma_{th}=27.56$ in *Acts*→*Luke* – indicate that the readers addressed by these texts may even coincide, as far as their STM capacity is concerned.

The example just discussed illustrates the following point. Since $M_F=P_F/I_P$, I–channels with similar $<M_F>$ – like in the above example, namely $<M_F>=2.89$ in *Luke*, $<M_F>=2.91$ in *Acts* – and I_P rarely can exceed the upper value (9) of Miller's law [52], as sentences get long the writer – who is, of course, also a reader of his/her own text – unconsciously introduces more interpunctions, therefore limiting I_P in Millers' range [1]. Consequently $<I_P>$ is longer in *Acts* (8.77) than in *Luke* (7.11).

Hebrews and *Apocalypse* are completely disconnected with the other NT in the S–channel but not with each other. These two texts unexpectedly coincide in the S–channels, both in slope and correlation coefficient (Tables 7,8). This coincidence produces very large signal–to–noise ratios (Tables 5,6), namely $\Gamma_{th}=42.61$ dB in *Hebrews*→*Apocalypse* and $\Gamma_{th}=42.68$ in *Apocalypse*→*Hebrews*, practically the same value (i.e. about 18,500 in linear units). The texts share the same style – $<P_F>=32$ in *Hebrews* and $<P_F>=30.70$ in *Apocalypse* – therefore the two data sets, in this channel, seem to be produced by the same source.

In the I–channel *Hebrews* and *Apocalypse* are also completely disconnected with the other NT texts but they are each other significantly connected because $\Gamma_{th}=15.25$ dB in *Hebrews*→*Apocalypse* and $\Gamma_{th}=13.92$ in *Apocalypse*→*Hebrews*.

Finally, notice that the four gospels are closer to each other than to the other texts.

Table 7. Theoretical slope and correlation coefficient of the regression line according to Section 4, for the indicated input texts. Output Channel: *Hebrews*. Notice that 5 decimal digits are reported for *Apocalypse* because its value is very close to 1.

Text	Sentences vs Sentences	%	Interpunctions vs Interpunctions	
	m_{jk}	r_{jk}	m_{jk}	r_{jk}
Matthew	0.6614	0.9576	1.5023	0.9891
Mark	0.6245	0.9833	1.6050	0.9990
Luke	0.6733	0.9837	1.4479	0.9983
John	0.6120	0.9737	1.5289	0.9905
Acts	0.8136	0.9897	1.5067	0.9977
Apocalypse	0.9941	0.99999	1.0895	0.9865

Table 8. Theoretical slope and correlation coefficient of the regression line according to Section 4, for the indicated input texts. Output Channel: *Apocalypse*. Notice that 5 decimal digits are reported for *Hebrews* because its value is very close to 1.

Text	Sentences vs Sentences		Interpunctions vs Interpunctions	
	m_{jk}	r_{jk}	m_{jk}	r_{jk}
Matthew	0.6654	0.9589	1.3789	0.9516
Mark	0.6283	0.9841	1.4731	0.9929
Luke	0.6774	0.9845	1.3290	0.9754
John	0.6157	0.9747	1.4033	0.9547
Acts	0.8184	0.9903	1.3829	0.9731
Hebrews	1.0060	0.99999	0.9179	0.9865

5.2. Greek Literature

For the Greek Literature, Table 9 reports the slope m and the correlation coefficient r of the regression lines between n_S versus n_W, and n_I versus n_S. Table 10 (S–channels) and Table 11 (I–channels) report Γ_{th}. The data referring to *John* are also reported for comparing it to Aesop's *Fables*, because of their vicinity in the vector plane, Figure 1.

Table 9. Slope m and the correlation coefficient r of the regression lines between n_S versus n_W, and n_I versus n_S for the indicated texts of the Greek Literature. Slope and correlation coefficients have been calculated as those reported in Table xx.

Author	n_S versus n_W		n_I versus n_S	
	m	r	m	r
Polybius	0.0343	0.9971	3.2432	0.9885
Plutarch	0.0371	0.9195	3.3539	0.9577
Flavius Josephus	0.0325	0.9734	3.1891	0.9846
Aesop	0.0545	0.9032	3.4236	0.9302
John	0.0549	0.9181	2.6797	0.9517

Table 10. S–channel, Greek Literature. Theoretical signal–to–noise ratio Γ_{th} (dB) in the channel between the (input) text indicated in the first column and the (output) text indicated in the first line. For example, if the input is *Polybius* and the output is *Plutarch*, then Γ_{th} = 9.81; vice versa if the input is *Plutarch* and the output is *Polybius*, then Γ_{th} = 8.48.

Text	Polybius	Plutarch	Flavius	Aesop	John
Polybius	∞	8.48	16.08	1.42	1.78
Plutarch	9.81	∞	14.12	6.51	6.38
Flavius Josephus	15.19	12.24	∞	2.30	2.47
Aesop	7.08	9.89	7.46	∞	28.61
John	7.28	9.78	7.51	28.74	∞

Table 11. I–channel, Greek Literature. Theoretical signal–to–noise ratio Γ_{th} (dB) in the channel between the (input) text indicated in the first column and the (output) text indicated in the first line. For example, if the input is *Polybius* and the output is *Plutarch*, then Γ_{th} = 17.06; vice versa if the input is *Plutarch* and the output is *Polybius*, then Γ_{th} = 16.49.

Text	Polybius	Plutarch	Flavius	Aesop	John
Polybius	∞	16.49	30.80	12.15	13.19
Plutarch	17.06	∞	18.32	21.07	13.91
Flavius Josephus	30.56	17.51	∞	12.77	14.11
Aesop	13.07	21.42	13.94	∞	13.04
John	10.84	11.94	12.02	10.77	∞

Let us examine the connection of *John* with *Fables*. Figure 6 shows the scatterplots and regression lines between n_W (words, independent variable) and n_S (sentences, dependent variable) in *John* (cyan triangles and cyan) and in *Aesop* (magenta circles and magenta line). Notice that the two regression lines are practically superposed and the scattering of the two sets are very alike.

Figure 7 shows the scatterplot and regression line between n_S (sentences, independent variable) and n_I (interpunctions, dependent variable) in *John* (cyan triangles and cyan) and in *Aesop* (magenta circles and magenta line). In this case, it is clear they do not share the slope.

Table 9 reports slope and correlation coefficient of the regression lines. From these data we calculate Γ_{th}, according to Section 4, reported in Table 10 (S-channels) and Table 11 (I-channels)

John and *Aesop* share a large Γ_{th} in the S–channel and a significant Γ_{th} in the I–channel, therefore, this “fine tuning” clarifies that the vicinity of the two ending points in Figure 1 is mainly due to sharing more the style than readers’ STM capacity.

In conclusion, S–channel results suggest that *John*’s style was likely affected by *Fables*, or by the particular kind of story–telling, while the I–channel results suggest that *John*’s readers were not different, as far as the STM capacity, from the readers of the other texts listed (see the last column in Table 11.

As for the historians, Flavius Josephus shares more the style of Polybius than that of the other writers (Table 10) and that to his readers is required the same STM capacity of

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Polybius' readers, since $\Gamma_{th} = 30.80$ in the I–channel *Polybius → Flavius Josephus* and $\Gamma_{th,dB} = 30.56$ in *Flavius Josephus→Polybius* (Table 11).

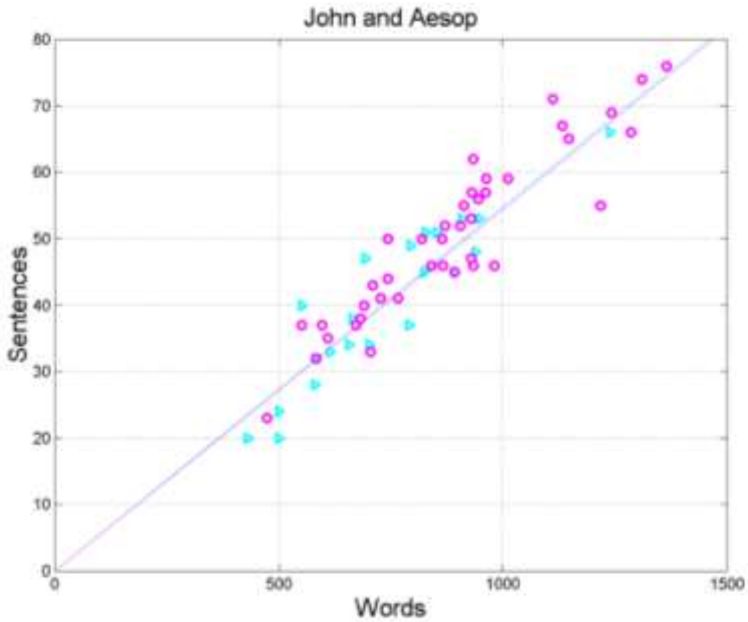

Figure 6. Scatterplots and regression lines between n_W (words, independent variable) and n_S (sentences, dependent variable) in *John* (cyan triangles and cyan) and in *Aesop* (magenta circles and magenta line). Notice that the two regression lines are practically superposed and the scattering of the two sets are very alike.

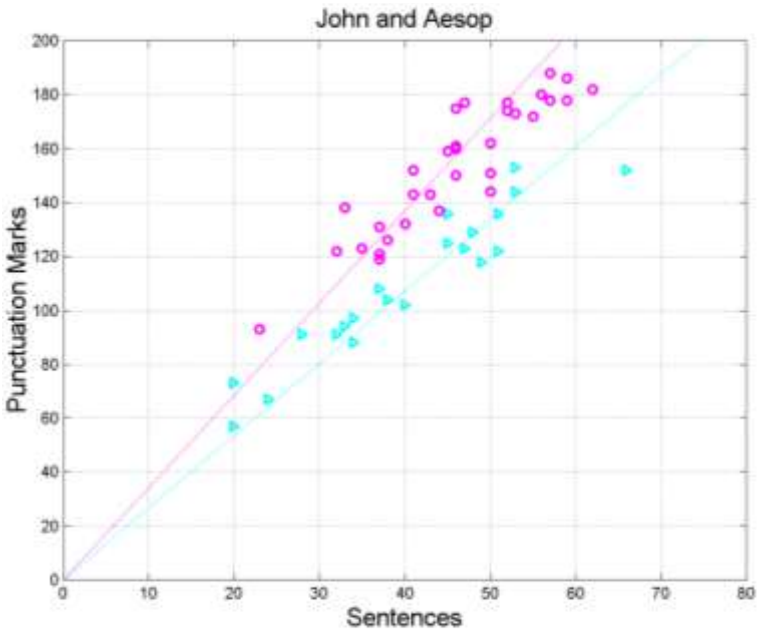

Figure 7. Scatterplots and regression lines between n_S (sentences, independent variable) and n_I (interpunctions, dependent variable) in *John* (cyan triangles and cyan) and in *Aesop* (magenta circles and magenta line).

5.3. Issues and solutions

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At this stage, however, as discussed in Reference [3], important issues arise likely due to the small sample size used in calculating the regression line parameters, especially for the NT texts, and some questions must be answered.

The large and unexpected Γ_{th} in the channels *Hebrews*↔*Apocalypse* is just due to chance or is it due to real likeness of the two texts? How can we assess whether these values are reliable? Now, it is practically impossible to estimate some probabilities of the parameters m and r of the regression lines of Table 3 because the texts available are very few. If Matthew had written, say, hundreds of texts, then we could attempt an analysis based on probability, but this is not the case, of course, and we are in the same situation for many ancient or modern authors.

In fact, because of the small sample size used in calculating a regression line, the slope m and the correlation coefficient r – being stochastic parameters – are characterized by mean values and standard deviations which depend on the sample size [9]. Obviously, the theory would yield more precise estimates of the signal–to–noise ratio Γ_{th} for larger sample size, as it can be assumed for the Greek Literature.

With a small sample size, the standard deviations of m and r can give too large a variation in Γ_{th} (see the sensitivity of this parameter to the slope m and the correlation coefficient r in [3]). To avoid this inaccuracy – due to small sample size, not to the theory of Section 4 – we have defined and discussed [3, 4] a "renormalization" of the texts, and their subsequent analysis, based on Monte Carlo (MC) simulations of multiple texts attributed to the same writer, whose results can be considered "experimental". Therefore, in the cases of texts with small sample size for which we suspect Γ_{th} is due only to chance, as it may be with *Hebrews* and *Apocalypse*, the results of the simulation can replace the theoretical values.

Besides the usefulness of the simulation as a "renormalization" tool, there is another property – very likely more interesting –, of the generated new texts. In fact, since the mathematical theory does not consider meaning, these new texts could have been "written" by the author, because they maintain the main statistical properties of the original text. In other words, they are "literary texts" that the author might have written at the time when he/she wrote the original text. Based on this hypothesis we can consider a large number of texts for each author. With this strategy, we think we have solved these issues in Reference [3]. In the next section we recall the rationale of the MC simulation.

6. S–channels and I–channels: Experimental signal–to–noise ratio Γ_{ex}

In this section, after recalling the Monte Carlo simulation steps to obtain the new texts attributed to the same author, we examine S–channels and I–channels.

6.1. Multiple versions of a text: Monte Carlo simulation

Let the literary text Y_j be the "output" of which we consider n disjoint block–texts (e.g., chapters) and let us compare it with a particular input literary text Y_k characterized by a regression line, as detailed in Section 4. The steps of the MC simulation are the following (here explicitly described for S–channels):

1. Generate n independent integers (the number of disjoint block–texts, e.g. chapters, 28 in *Matthew*) from a discrete uniform probability distribution in the range 1 to n, with replacement – i.e., a block–text can be selected more than once.
2. "Write" another "text Y_j" with new n block–texts, e.g. the sequence 2; 1; n; $n-2$, hence take block–text 2, followed by block–text 1, block–text n, block–text $n-2$ up to n block–texts. A block–text can appear twice (with probability $1/n^2$), three times (with probability $1/n^3$), etc., and the new "text Y_j" can contain a number of words greater or smaller than the original text, on the average; however, differences are small and do not affect the final statistical results and analysis.
3. Calculate the parameters m_j and r_j of the regression line between words (independent variable) and sentences (dependent variable) in the new "text Y_j", namely Equation (1).
4. Compare m_j and r_j of the new "text Y_j" (output, dependent text) with any other text (input, independent text, m_k and r_k), in the "cross–channels" so defined, including the original text Y_j (this latter case referred to as the "self–channel").
5. Calculate m_{jk}, r_{jk} and $\Gamma_{cross,ex}$ of the cross–channels or $\Gamma_{self,ex}$ of the self–channel according to the theory of Section 4.
6. Consider the signal–to–noise ratios obtained as "experimental" results.
7. Repeat steps 1 to 6 many times for obtaining reliable results (we have repeated the sequence 5000 times, ensuring a standard deviation of the mean value less than about 0.1 dB).

In conclusion, the MC simulation substitutes a probability study on the joint density function of m and r on real texts, not available in such a large number. Let us now apply the MC simulation to the NT texts.

6.2. S–channels and I–channels

Figure 8 shows $<\Gamma_{ex,cross}>$ and $<\Gamma_{ex,self}>$ for each NT output text and input texts for S–channels (upper panel) and I–channels (lower panel). The mean and standard deviation numerical values are reported in Appendix A because they are needed in Section 7.

From Figure 8, for example, or from Appendix A, in S–channels we can notice that if the input is *Matthew* and the output is *Luke* (blue line) then $\Gamma_{cross,ex} = 20.52$, vice versa if the input is *Luke* and the output is *Matthew* (black line) then $\Gamma_{cross,ex} = 19.68$. If the input is *Matthew* and the output is *Matthew* (self–channel) then $\Gamma_{self,ex} = 25.01$. In this case we compare *Matthew* with 5000 "new" *Matthews* obtained randomly. Notice that $\Gamma_{self,ex} > \Gamma_{cross,ex}$.

The gospels are clearly distinguishable from the other texts, especially from *Hebrews* and *Apocalypse*, which can be each other confused. Notice that $\Gamma_{self,ex} = 15.66$ for *Hebrews* and $\Gamma_{self,ex} = 19.76$ for *Apocalypse* are always very similar to $\Gamma_{cross,ex} = 15.73$ and $\Gamma_{cross,ex} = 19.64$, respectively, therefore the theoretical striking similarity of the two texts found in Section 5 (Table 5) is confirmed.

Notice that the gospels differ quite significantly from *Acts*, *Hebrews* and *Apocalypse*, and that they are each other very similar, therefore confirming, with this "fine–tuning" the findings shown in Figure 1.

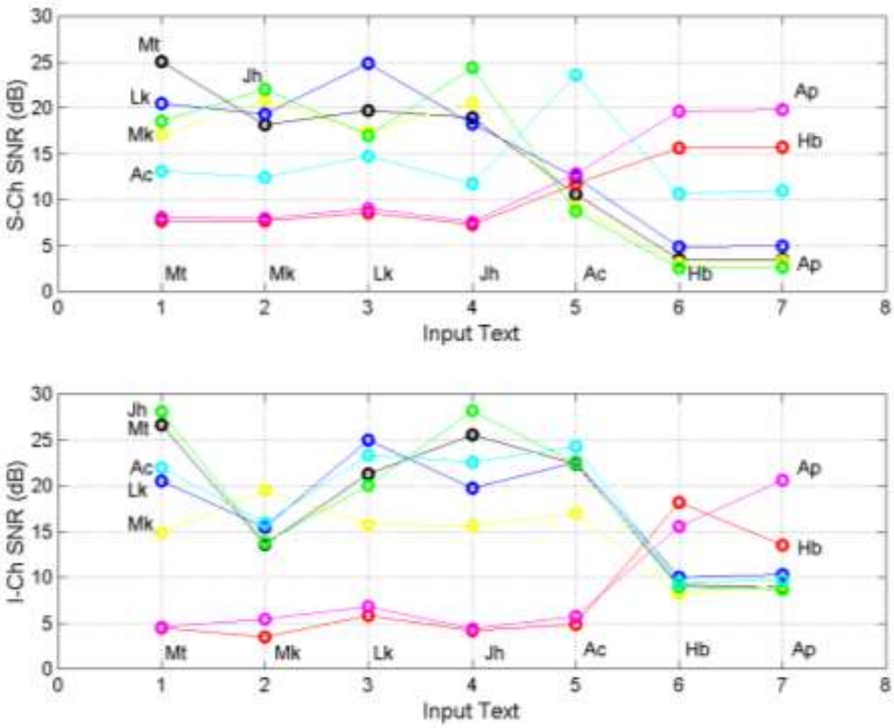


Figure 8. $< \Gamma_{ex,cross} >$ and $< \Gamma_{ex,self} >$ for each NT input texts indicated in abscissa. **Upper panel**: S–channel; **Lower panel**: I–channel. Output texts: *Matthew*: black; *Mark*: yellow; *Luke*: blue; *John*: green; *Acts*: cyan; *Hebrews*: red; *Apocalypse*: magenta. Mean and standard deviation numerical values are reported in Appendix A. Notice that $\Gamma_{ex,self} > \Gamma_{ex,cross}$.

Let us discuss the results for I–channels (lower panel). For example, if the input is *Matthew* and the output is *Luke* then $\Gamma_{cross,ex} = 20.46$ dB; vice versa if the input is *Luke* and the output is *Matthew*, then $\Gamma_{cross,ex} = 21.23$ dB. If the input is *Matthew* and the output is *Matthew* then $\Gamma_{self,ex} = 26.63$, very close to that obtained in the S–channel. Like in S–channels, $\Gamma_{self,ex} > \Gamma_{cross,ex}$.

The gospels are each other very similar and clearly distinguished from *Hebrews* and *Apocalypse*, confirming therefore also in this channel what is shown in Figure 1. Finally, notice that also in the I–channel *Hebrews* and *Apocalypse* are always the most similar texts.

In the next sub–section we compare $< \Gamma_{ex} >$ to $< \Gamma_{th} >$ because this comparison gives fundamental insight on the range in which $< \Gamma_{th} >$ is reliable.

6.3. Γ_{th} versus Γ_{ex} and minimum reliable range of Γ_{th}

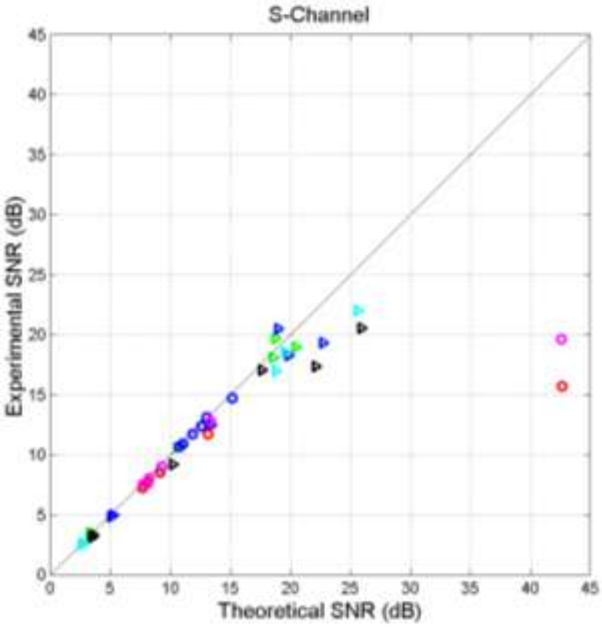
As done in Reference [3], it is very interesting to compare Γ_{th} to Γ_{ex}. This comparison gives the minimum range in which Γ_{th} is reliable.

Figure 9 shows $< \Gamma_{ex} >$ versus Γ_{th} in S–channels, for self– and cross–channels (a) and the difference $\Gamma_{th} - \Gamma_{ex}$ versus Γ_{th} (b). This difference represents the ratio (expressed in dB) between the noise power in the experimental channel and that in the theoretical channel. As in Reference [3], we notice that the two signal–to–noise ratios are very well correlated up to a maximum value set by $< \Gamma_{self,ex} >$, presently at about 20~22 dB (horizontal asymptote), beyond which $< \Gamma_{ex} >$ cannot follow the large increase in Γ_{th}, which reaches about 42 dB in *Hebrews* and *Apocalypse*.

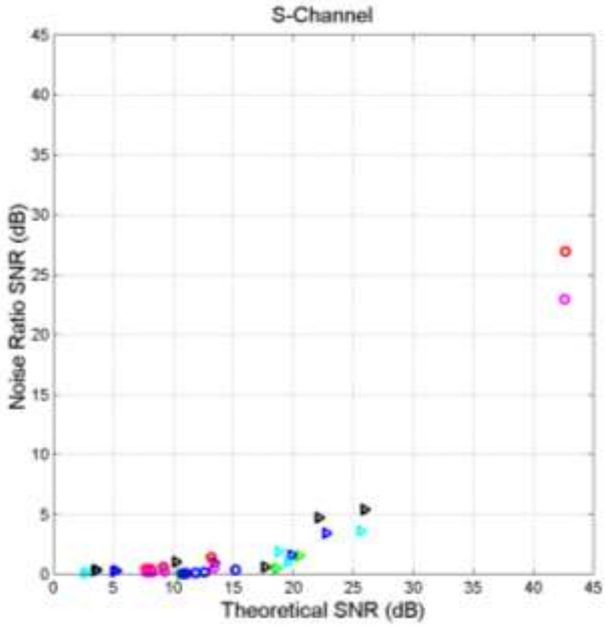
Figure 10 shows $< \Gamma_{ex} >$ versus Γ_{th} and $\Gamma_{th} - \Gamma_{ex}$ versus Γ_{th} in I–channels. We notice the same behavior of S–channels, but with set at about 24 dB.

From these figures we can draw the following conclusion.

1) There is a horizontal asymptote which sets the maximum reliable value of Γ_{th}, given by the largest $< \Gamma_{self,ex} >$.
2) In this range the MC simulation is not indispensable becasue Γ_{th}, calculated from Equation (12), is reliable. However, MC simulations are very useful to calculate the likeness index [3], which is based on a large number of texts an author might have written.
3) The theory can predict large values – as in *Hebrews* and *Apocalypse* – but we may suspect they are just due to chance because of the large sensitivity of Γ_{th} to slopes and correlation coefficients, as discussed in Reference [3]. Therefore, a cautionary (pessimistic) value is to assume $\Gamma_{th} \approx \Gamma_{ex}$.
4) The difference $\Gamma_{th} - \Gamma_{ex}$ – i.e, the ratio (expressed in dB) between the noise power in the experimental channel and that in the theoretical channel – tends to be constant before saturation; afterwards it increases linearly, therefore indicating the end of a reliable range of Γ_{th}.



(a)



(b)

Figure 9. S–channel. **(a)** Scatterplot of $< \Gamma_{ex} >$ versus Γ_{th} in S–channels; **(b)** Scatterplot of $\Gamma_{th} - \Gamma_{ex}$ versus Γ_{th}. *Matthew* (green triangles); *Mark* (black triangles); *Luke* (blue triangles); *John* (cyan triangles); *Acts* (blues circles); *Hebrews* (red circles); *Apocalypse* (magenta circles).

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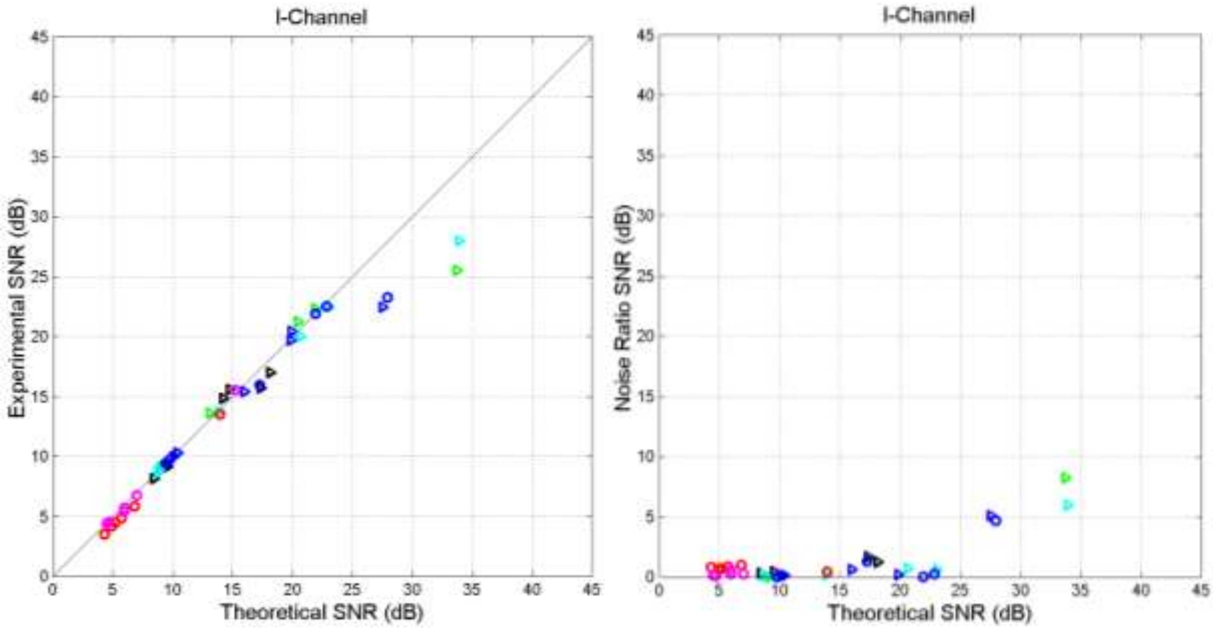

Figure 10. I–channel. **(a)** Scatterplot of $<\Gamma_{\mathrm{ex}}>$ versus Γ_{th} in S–channels; **(b)** Scatterplot of $\Gamma_{\mathrm{th}} - \Gamma_{\mathrm{ex}}$ versus Γ_{th}. *Matthew* (green triangles); *Mark* (black triangles); *Luke* (blue triangles); *John* (cyan triangles); *Acts* (blues circles); *Hebrews* (red circles); *Apocalypse* (magenta circles).

In the next section we calculate the likeness index of texts and define a useful graphical tool, the "channels quadrants".

7. Likeness index of texts and channels quadrants

In Reference [3] we explored a way of comparing the signal–to–noise ratios $\Gamma_{dB,ex}$ of self– and cross–channels objectively and possibly getting more insight on texts mathematical likeness. In comparing a self–channel with a cross–channel the probability of mistaken one text with another is a binary problem, because a decision must be taken between two alternatives. The problem is classical in binary digital communication channels affected by noise. In digital communication, "error" means that bit 1 is mistaken for bit 0 or vice versa, therefore the channel performance worsens as the error frequency (i.e., the error probability) increases. However, in linguistics self– and cross channels "error" means that a text can be more or less mistaken, or confused, with another text, consequently two texts are more similar as the "error probability" increases. Therefore, a large error probability means that two literary texts are mathematical similar.

We first recall the theory of likeness index and then define the "channels quadrants", a graphical tool which classifies texts, with the aim of showing how much writers' style and readers' STM capacity are matched.

7.1. Likeness Index

In digital communication channels affected by noise, the probability of error is given by [3]:

$$p_e = 0.5\left[\int_{T_{min}}^{\infty} g_0(\Gamma_{ex,cross})d\Gamma_{dB,ex,cross} + \int_{-\infty}^{T_{min}} g_1(\Gamma_{ex,self})d\Gamma_{ex,self}\right] \quad (13)$$

In Equation (13) $\Gamma_{ex,cross}$ and $\Gamma_{ex,self}$ are modelled as Gaussian density functions with mean and standard deviation given in Appendix A. The decision threshold, T_{min}, is given by the intersection of the two known probability density functions $g_o(y)$ (cross–channel) and $g_1(y)$ (self–channel). The integrals limits are fixed as shown because in general $\Gamma_{dB,cross} \leq \Gamma_{dB,self}$.

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If $p_e = 0$ there is no intersection between the two densities; their mean values are centered at $-\infty$ and $+\infty$, respectively, or the two densities have collapsed to Dirac delta functions. If $p_e = 0.5$ the two densities are identical, e.g., a self–channel is compared with itself. In conclusion, $0 \leq p_e \leq 0.5$, therefore, if $p_e = 0$ cross– and self– channels can be considered totally uncorrelated; if $p_e = 0.5 = p_{e,max}$, self and cross–channels coincide, the two texts are mathematically identical.

The likeness index I_L is defined by:

$$I_L = \frac{p_e}{p_{e,max}} \tag{14}$$

The likeness index ranges in $0 \leq I_L \leq 1$; $I_L = 0$ means totally uncorrelated texts, $I_L = 1$ means totally correlated texts.

7.2. Channels quadrants

Some insight on the "fine–tuning" – i.e., matching writers' style and readers' STM capacity – and on the relationship between texts can be visualized through the "channels quadrants" shown in Figure 11. In quadrant IV, the S–channels of two texts are significantly similar and the texts coincide along the vertical line $x = 1$. Similarly, in quadrant II, the I–channels are significantly similar and the texts coincide along the horizontal line $y = 1$. In quadrant III, the two texts can be considered unmatched completely uncorrelated at the origin (0,0). Finally, in quadrant I the two texts are very much matched in both channels and fully matched at (1,1), therefore at this point two texts are mathematically indistinguishable.

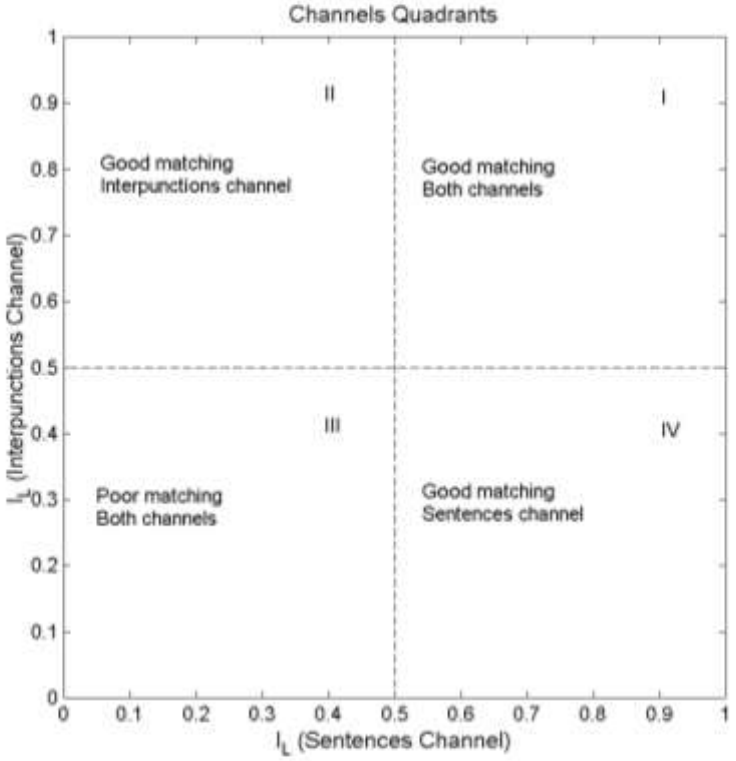

Figure 11. Matching texts in S-channels and in I-channels.

Figure 12 shows the scatterplot of I_L of the I–channel (ordinate) versus I_L of the S–channel (abscissa) referred to the NT. The numerical values are reported in Appendix B. We can notice that only 19.0% of the cases have good matching in both channels (quadrant I); 21.4% have good matching only in the I–channel (quadrant II); 54.8% have poor matching in both channels (quadrant III) and 4.8% have good matching only in the S–channel (quadrant IV).

The marginal probabilities are $P(I_L \geq 0.5) = 23.8\%$ in the S– channel and $P(I_L \geq 0.5) = 40.4\%$ in the I–channel. This fact, together with the other percentages mark some interesting differences between S–channels and I–channels.

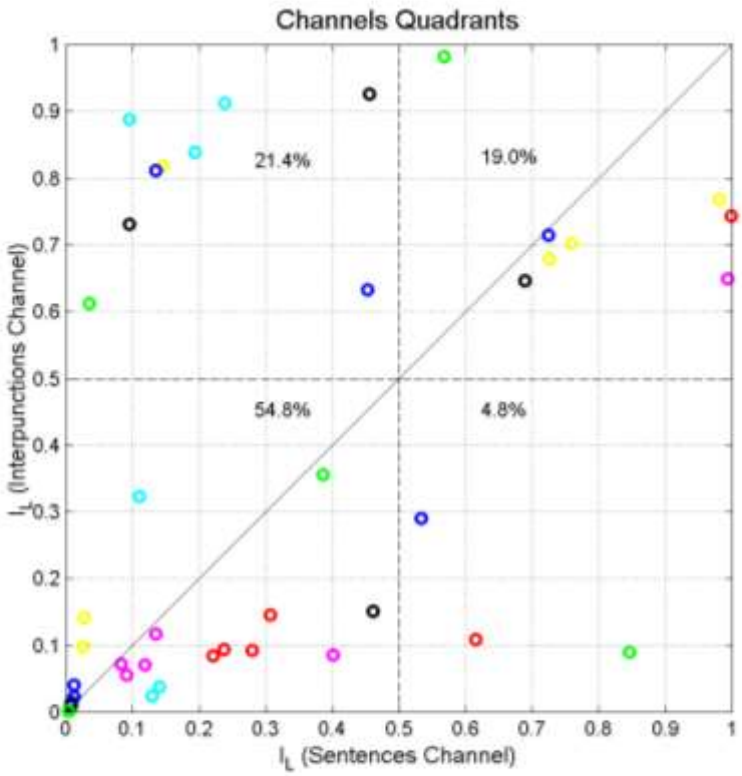

Figure 12. Scatterplot of I_L of the Interpunctions channel (ordinate scale) versus I_L of the S–channel (abscissa scale). Output channels (first line in Tables 11, 12): *Matthew*: black circles; *Mark*: yellow; *Luke*: blue; *John*: green; *Acts*: cyan; *Hebrews*: red; *Apocalypse*: magenta. Percentages indicate the relative number of cases falling in a quadrant.

Tables 12, 13 report the average value of I_L of the two asymmetric channels (e.g., *Matthew*→*Luke* and *Luke*→*Matthew*, see Appendix B) in S–channels and in I–channels, respectively.

For S–channels, we notice a large $I_L = 0.707$ between *Matthew* and *Luke*; a very large $I_L = 0.914$ between *Mark* and *John*, and a very large and unexpected $I_L = 0.996$ between *Hebrews* and *Apocalypse*. All these values are reliable because they are based on Γ_{th}.

We can notice that the mathematical similarity of *Matthew* and *Luke*, already observed, is further reinforced by noting they are quite similar in both channels. Another interesting fact to notice is the high likeness index between *Mark* and *John* who, according to scholars [64,65], share some similar Greek.

For I–channels there are confirmation and differences compared to S–channels. Recall that I–channels are more concerned with readers' STM memory than with authors' style. The large I_L between *Hebrews* and *Apocalypse* of the S–channel is not confirmed in the I–channel, although it is large enough ($I_L = 0.697$) to link the two groups of readers.

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Table 12. Average value of I_L in S–channels. For example, in the channels *Hebrews*↔*Apocalypse*, from Appendix B we get the average value $(0.993 + 0.999)/2 = 0.996$. In bold type the cases in which $I_L > 0.5$.

	Mt	**Mk**	**Lk**	**Jh**	**Ac**	**Hb**	**Ap**
Mt	1						
Mk	0.160	1					
Lk	**0.707**	**0.630**	1				
Jh	**0.511**	**0.914**	0.419	1			
Ac	0.145	0.128	0.188	0.066	1		
Hb	0.144	0.132	0.160	0.133	0.372	1	
Ap	0.063	0.059	0.074	0.044	0.271	**0.996**	1

Table 13. Average value of I_L in I–channels. In bold type the cases in which $I_L > 0.5$.

	Mt	**Mk**	**Lk**	**Jh**	**Ac**	**Hb**	**Ap**
Mt	1						
Mk	0.427	1					
Lk	**0.681**	0.485	1				
Jh	**0.954**	0.429	0.494	1			
Ac	**0.785**	**0.571**	**0.863**	**0.750**	1		
Hb	0.051	0.096	0.084	0.037	0.067	1	
Ap	0.043	0.099	0.079	0.037	0.062	**0.697**	1

Very insightful is the large $I_L = 0.863$ between *Luke* and *Act*, both texts written by Luke, who very likely addressed, as already mentioned, similar groups of readers. Further, notice that *Acts* is very close to all other texts, except *Hebrew* and *Apocalypse*, which means that *Acts* likely addressed all the early Christians.

Finally, let us reconsider the vicinity of *John* to Aesop's *Fables* shown in Figure 1. The signal–to–noise ratio in the S–channel *Aesop*→*John* is $\Gamma_{cross,ex} = 23.23$, with standard deviation 6.7 – John's self–channel values are given in Appendix A – giving therefore $I_L = 0.930$. In the I–channel, $\Gamma_{cross,ex} = 19.91$ with with standard deviation 0.70 dB, therefore $I_L = 0.150$.

In brief, *John*'s style is similar to *Aesop*'s style – see also the values $< P_F >= 18.56$ in *John*, $< P_F >= 18.29$ in *Fables* – but readers' STM capacity is not, also evident in the values $< I_P >= 6.79$ in *John*, $< I_P >= 5.28$ in *Fables*, a difference which implies a diverse readability index (see Tables 1,2).

In conclusion, the coincidence of *John* and *Aesop* in Figure 1 is a necessary condition for being similar, but only the fine tuning provided by linguistic channels can fully reveal the nature of this similarity. In this example, *John* might have been inspired by the long tradition of short stories telling a truth, such as Aesop' *Fables*.

7.3 I–channel versus S–channel: Hebrews and *Apocalypse*

According to Tables 12 and 13 *Hebrews* and *Apocalypse* are mathematically each other "photocopy" in the S–channel and very similar in the I–channel, therefore the style – as it is meant in this paper – of the two authors coincide and their readers share similar STM capacity. As already mentioned, the likeness of these texts is unexpected therefore, it may be realistic to suppose that the writers and readers of them have belonged to the same group of Jewish–Christians, an issue to be researched by scholars of the Greek language used in the NT and by historians of the early Christianity.

In conclusion, the S–cannel and the I–channel describe the deep mathematical joint structure of two texts, namely authors' style and readers' STM capacity required to read the texts. If both likeness indices are large, then two texts are very similar. These mathematical results may be used to confirm, in a multidisciplinary approach, what scholars of humanistic disciplines find and they can even suggest new paths of research, such as the relationship between the author and readers of *Hebrews* and *Apocalypse*.

8. Synthesis of main results

At this point the reader of the present paper may be overwhelmed by tables and figures. However, due to the nature of the mathematical theory based on studying regression lines and linguistic channels – not to mention the many comparisons that can be done, even in a small literary corpus as is the New Testament – these numbers and figures are the only means we know for supporting the partial conclusions reached in each section above. Now we can attempt to present a final compact comparison based on one more table and figure.

Table 14 shows the most synthetic comparison of the NT texts, namely the overall mean value of $\boldsymbol{I_L}$, averaged from Tables 12, 13. By assuming $\boldsymbol{I_L > 0.5}$ as the threshold beyond which texts are reasonable similar, this threshold is exceeded in *Luke–Matthew*, *Luke–Mark*, *John–Matthew*, *John–Mark*, *Luke–Acts*.

The couple *Hebrews–Apocalypse* is completely disconnected from the other texts and their likeness index is the largest. We like to reiterate that these two texts deserve further studies by historians of the early Christian Church Literature at the higher level of meaning, readers and possible Old Testament texts that might have affected them, a task well beyond the knowledge of the present author.

Table 14. Overall total average value of I_L. For example, in the channels *Hebrews*↔*Apocalypse*, from Tables 12,13 we get the average value $(0.996 + 0.697)/2 = 0.847$. In bold type the cases in which $I_L > 0.5$.

	Mt	**Mk**	**Lk**	**Jh**	**Ac**	**Hb**	**Ap**
Mt	1						
Mk	0.294	1					
Lk	**0.694**	**0.558**	1				
Jh	**0.733**	**0.674**	0.457	1			
Ac	0.465	0.350	**0.526**	0.408	1		
Hb	0.098	0.114	0.122	0.085	0.220	1	
Ap	0.053	0.079	0.077	0.041	0.167	**0.847**	1

Now, we show that the value $\boldsymbol{I_L \approx 0.5}$ brings a special meaning, besides defining the borders of the quadrants in Figure 12.

Figure 13 shows the scatterplot between $\boldsymbol{I_L}$ of S–channels and I–channels versus the difference $\boldsymbol{\Delta\Gamma} =< \boldsymbol{\Gamma_{self,ex}} > - < \boldsymbol{\Gamma_{cross,ex}} >$ found in each channel, for all NT texts. The scatterplot suggests a tight inverse proportional relationship between $\boldsymbol{I_L}$ and $\boldsymbol{\Delta\Gamma}$. A very similar scatterplot and tight relationship was also found for texts taken from the Italian Literature [4], therefore suggesting that this relationship is "universal" for alphabetical texts.

The best–fit non–linear curve drawn in Figure 13 can be considered a good overall model, given by:

$$\boldsymbol{I_L} = \mathbf{exp}\left(-\frac{\mathbf{10^{\Delta\Gamma/10}-1}}{\mathbf{5}}\right) \quad (15)$$

Notice that $\boldsymbol{\Delta\Gamma}$ is the ratio (expressed in dB) between the noise, defined in Section 4, affecting a cross–channel and that found in the corresponding self–channel.

The value $\boldsymbol{I_L} = \mathbf{0.5}$ is obtained from Equation (15) at $\boldsymbol{\Delta\Gamma} = \mathbf{6.50}$ dB, a value which is practically the standard deviation of $\boldsymbol{\Gamma_{self,ex}}$ in all cases, because this parameter ranges from 6 to 7.

We can link this last observation to the quadrants of Figure 11. As a general rule, we can say that in Quadrant I ($\boldsymbol{I_L} > \mathbf{0.5}$ in both channels) we will always find texts whose $< \boldsymbol{\Gamma_{cross,ex}} >$ is approximately distant $\mathbf{6{\sim}7}$ dB from the corresponding $< \boldsymbol{\Gamma_{self,ex}} >$. In other words, a noise power ratio of $\mathbf{6{\sim}7}$ dB indicates that the two texts considered tend to be matched in both channels, therefore it can be taken, with the vector representation of Figure 1, as a first objective assessment of texts likeness.

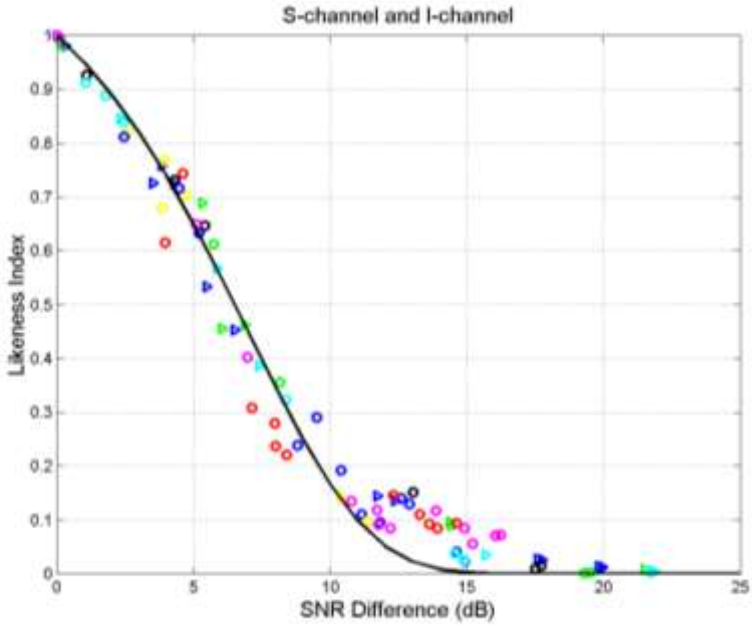

Figure 13. Scatterplot of I_L of S–channel and I–channel versus $\Gamma_{self,ex} - \Gamma_{cross,ex}$. *Matthew* (green triangles); *Mark* (black triangles); *Luke* (blue triangles); *John* (cyan triangles); *Acts* (blues circles); *Hebrews* (red circles); *Apocalypse* (magenta circles). The black line draws Equation (15).

9. Conclusion

We have studied two fundamental linguistic channels – namely the S–channel and the I–channel – and have shown that they can reveal deeper connections between texts. As study–case, we have considered the Greek New Testament, with the purpose of determining mathematical connections between its texts and possible differences in writing style (mathematically defined) of writers, and in reading skill required to their readers. The analysis is based on deep–language parameters and communication/information theory developed in previous papers.

Our theory does not follow the actual paradigm of linguistic studies, which neither consider Shannon's communication theory, nor the fundamental connection that some linguistic parameters have with reading skill and short–term memory capacity of readers.

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To set the New Testament texts in the Greek Classical Literature, we have also studied and compared texts written by Aesop, Polybius, Flavius Josephus and Plutarch.

We have found large similarity (measured by the likeness index) in the couples of texts *Luke–Matthew*, *Luke–Mark*, *John–Matthew*, *John–Mark*, *Luke–Acts*, findings that largely confirm what scholars have found about these texts, therefore giving credibility to the theory.

The gospel according to *John* is very similar to Aesop' *Fables*. *John* might have been inspired by the long tradition of short stories telling a truth, such as *Fables.*

Surprisingly, we have found that *Hebrews* and *Apocalypse* are each other "photocopy" in the two linguistic channels, and not linked to all other texts. In our opinion, these two texts deserve further studies by historians of the early Christian Church Literature conducted at the higher level of meaning, readers and possible Old Testament texts which might have influenced them, a task well beyond the knowledge of the present author.

Appendix A. Signal–to–noise ratio in S–channels and in I–channels

Table A1 reports $< \Gamma_{ex} >$ (dB) and its standard deviation (dB, in parentheses) in the S–channel between the (input) text indicated in the first column and the (output) text indicated in the first line. For example, if the input is *Matthew* and the output is *Luke* (cross–channel) then $\Gamma_{dB,ex} = 28.52$; vice versa if the input is *Luke* and the output is *Matthew*, then $\Gamma_{ex} = 19.68$. If the input is *Matthew* and the output is *Matthew* (self–channel) then $\Gamma_{ex} = 25.01$.

Table A.1 S–channels. Experimental mean signal–to–noise ratio Γ_{ex} (dB) and standard deviation (dB, in parentheses) in the channel between the (input) text indicated in the first column and the (output) text indicated in the first line.

	Mt	**Mk**	**Lk**	**Jh**	**Ac**	**Hb**	**Ap**
Mt	25.01 (6.96)	17.06 (5.94)	20.52 (5.81)	18.52 (4.24)	13.15 (2.34)	7.69 (1.81)	8.05 (1.48)
Mk	18.12 (3.46)	20.91 (7.13)	19.33 (3.46)	22.05 (6.04)	12.40 (1.43)	7.66 (1.33)	8.00 (1.01)
Lk	19.68 (6.43)	17.39 (4.75)	24.82 (6.53)	16.98 (2.73)	14.75 (2.06)	8.54 (1.67)	9.00 (1.31)
Jh	18.95 (2.72)	20.59 (7.04)	18.30 (3.16)	24.39 (7.07)	11.73 (1.47)	7.27 (1.33)	7.58 (1.04)
Ac	10.61 (2.16)	9.19 (1.71)	12.45 (2.24)	8.71 (0.96)	23.55 (6.16)	11.71 (3.29)	12.79 (2.74)
Hb	3.52 (1.43)	3.15 (1.28)	4.85 (1.64)	2.50 (0.81)	10.67 (2.64)	15.66 (6.77)	19.64 (6.86)
Ap	3.52 (1.44)	3.30 (1.28)	5.00 (1.66)	2.65 (0.81)	10.95 (2.69)	15.73 (6.69)	19.76 (6.74)

Table A2 reports $< \Gamma_{ex} >$ (dB) and its standard deviation (dB, in parentheses) in the I–channel between the (input) text indicated in the first column and the (output) text indicated in the first line.

For example, if the input is *Matthew* and the output is *Luke* (cross–channel) then $\Gamma_{dB,ex} = 20.46$; vice versa if the input is *Luke* and the output is *Matthew*, then $\Gamma_{ex} = 21.23$. If the input is *Matthew* and the output is *Matthew* (self–channel) then $\Gamma_{ex} = 26.63$, very close to that obtained in the S–channel.

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Table A.2 I–channels. Experimental mean signal–to–noise ratio $\Gamma_{dB,ex}$ (dB) and standard deviation (dB, in parentheses) in the channel between the (input) text indicated in the first column and the (output) text indicated in the first line.

	Mt	Mk	Lk	Jh	Ac	Hb	Ap
Mt	26.63 (6.68)	14.84 (5.68)	20.46 (5.83)	28.01 (5.92)	21.91 (5.81)	4.49 (1.60)	4.57 (2.35)
Mk	13.61 (2.80)	19.55 (7.32)	15.41 (3.01)	13.78 (2.60)	15.94 (2.87)	3.50 (2.10)	5.40 (1.56)
Lk	21.23 (5.40)	15.71 (4.22)	24.92 (6.57)	20.03 (3.22)	23.28 (5.45)	5.82 (2.01)	6.76 (2.40)
Jh	25.55 (6.17)	15.62 (6.38)	19.72 (4.86)	28.19 (6.15)	22.55 (6.32)	4.19 (1.57)	4.39 (2.46)
Ac	22.32 (6.00)	16.98 (5.69)	22.48 (5.14)	22.46 (5.28)	24.32 (6.26)	4.84 (1.80)	5.71 (2.20)
Hb	9.15 (0.54)	8.16 (0.66)	10.00 (0.54)	8.89 (0.37)	9.43 (0.82)	18.11 (7.14)	15.53 (5.00)
Ap	8.93 (0.97)	9.17 (0.94)	10.31 (1.07)	8.68 (0.60)	9.75 (1.20)	13.50 (6.97)	20.61 (6.88)

Appendix B. Likeness index in S–channels and in I–channels

Table B1 reports I_L in the S–channel between the (input) text indicated texts. For example, if the input is *Matthew* and the output is *Luke*, then $I_L = 0.724$; vice versa, if the input is *Mark* and the output is *Matthew*, then $I_L = 0.689$. Self–channels yield $I_L = 1$.

Table B1. S–channels. Mean value of the Likeness Index I_L in the channel between the (input) text indicated in the first column and the (output) text indicated in the first line.

	Mt	Mk	Lk	Jh	Ac	Hb	Ap
Mt	1	0.758	0.724	0.567	0.193	0.279	0.119
Mk	0.462	1	0.534	0.846	0.111	0.238	0.091
Lk	0.689	0.726	1	0.386	0.239	0.308	0.135
Jh	0.455	0.981	0.453	1	0.096	0.221	0.084
Ac	0.096	0.145	0.136	0.036	1	0.615	0.402
Hb	0.008	0.026	0.012	0.004	0.129	1	0.993
Ap	0.008	0.027	0.013	0.004	0.140	0.999	1

Table B2 reports I_L in the I–channel between the (input) text indicated texts. For example, if the input is *Matthew* and the output is *Luke*, then $I_L = 0.716$ dB; vice versa, if the input is *Luke* and the output is *Matthew*, then $I_L = 0.646$. Self–channels yield $I_L = 1$.

Table B2. I–channels. Mean value of the Likeness Index I_L in the channel between the (input) text indicated in the first column and the (output) text indicated in the first line.

	Mt	Mk	Lk	Jh	Ac	Hb	Ap
Mt	1	0.702	0.716	0.982	0.839	0.093	0.071
Mk	0.152	1	0.290	0.090	0.324	0.094	0.056
Lk	0.646	0.679	1	0.356	0.913	0.146	0.117
Jh	0.927	0.768	0.633	1	0.888	0.085	0.072
Ac	0.731	0.818	0.812	0.612	1	0.110	0.085
Hb	0.010	0.098	0.023	0.002	0.025	1	0.650
Ap	0.015	0.142	0.041	0.003	0.038	0.744	1

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