FontCode: Embedding Information in Text Documents using Glyph Perturbation

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Among many applications enabled by our FontCode method, here we create a poster embedded with an unobtrusive optical barcode (left). The poster uses text fonts that look almost identical from the standard Times New Roman, and has no traditional black-and-white barcode pattern. But our smartphone application allows the user to take a snapshot (right) and decode the hidden message, in this case, a Youtube link (middle).

We introduce FontCode, an information embedding technique for text documents. Provided a text document with specific fonts, our method embeds user-specified information in the text by perturbing the glyphs of text characters while preserving the text content. We devise an algorithm to choose unobtrusive yet machine-recognizable glyph perturbations, leveraging a recently developed generative model that alters the glyphs of each character continuously on a font manifold. We then introduce an algorithm that embeds a user-provided message in the text document and produces an encoded document whose appearance is minimally perturbed from the original document. We also present a glyph recognition method that recovers the embedded information from an encoded document stored as a vector graphic or pixel image, or even on a printed paper. In addition, we introduce a new error-correction coding scheme that rectifies a certain number of recognition errors. Lastly, we demonstrate that our technique enables a wide array of applications, using it as a text document metadata holder, an unobtrusive optical barcode, a cryptographic message embedding scheme, and a text document signature.

Additional Key Words and Phrases: Font manifold, glyph perturbation, error correction coding, text document signature

1 INTRODUCTION

Information embedding, the technique of embedding a message into host data, has numerous applications: Digital photographs have metadata embedded to record such information as capture date, exposure time, focal length, and camera’s GPS location. Watermarks embedded in images, videos, and audios have been one of the most important means in digital production to claim copyright against piracies [Bloom et al. 1999]. And indeed, the idea of embedding information in light signals has grown into an emerging field of visual light communication (e.g., see [Jo et al. 2016]).

In all these areas, information embedding techniques meet two desiderata: (i) the host medium is minimally perturbed, implying that the embedded message must be minimally intrusive; and (ii) the embedded message can be robustly recovered by the intended decoder even in the presence of some decoding errors.

Remaining elusive is the information embedding technique for text documents, in both digital and physical form. While explored by many previous works on digital text steganography, information embedding for text documents is considered more challenging to meet the aforementioned desiderata than its counterparts for images, videos, and audios [Agarwal 2013]. This is because the “pixel” of a text document is individual letters, which, unlike an image...

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pixel, cannot be changed into other letters without causing noticeable differences. Consequently, existing techniques have limited information capacity or work only for specific digital file formats (such as PDF or Microsoft Word).

We propose FontCode, a new information embedding technique for text documents. Instead of changing text letters into different ones, we alter the glyphs (i.e., the particular shape designs) of their fonts to encode information, leveraging the recently developed concept of font manifold [Campbell and Kautz 2014] in computer graphics. Thereby, the readability of the original document is fully retained. We carefully choose the glyph perturbation such that it has a minimal effect on the typeface appearance of the text document, while ensuring that glyph perturbation can be recognized through Convolutional Neural Networks (CNNs). To recover the embedded information, we develop a decoding algorithm that recovers the information from an input encoded document—whether it is represented as a vector graphics file (such as a PDF) or a rasterized pixel image (such as a photograph).

Exploiting the features specific to our message embedding and retrieval problems, we further devise an error-correction coding scheme that is able to fully recover embedded information up to a certain number of recognition errors, making a smartphone into a robust FontCode reader (see Fig. 1).

Applications. As a result, FontCode is not only an information embedding technique for text documents but also an unobtrusive tagging mechanism, finding a wide array of applications. We demonstrate four of them. (i) It serves as a metadata holder in a text document, which can be freely converted to different file formats or printed on paper without loss of the metadata—across various digital and physical forms, the metadata is always preserved. (ii) It enables to embed in a text unobtrusive optical codes, ones that can replace optical barcodes (such as QR codes) in artistic designs such as posters and flyers to minimize visual distraction caused by the barcodes. (iii) By construction, it offers a basic cryptographic scheme that not only embeds but also encrypts messages, without resorting to any additional cryptosystem. And (iv) it offers a new text signature mechanism, one that allows to verify document authenticity and integrity, regardless of its digital format or physical form.

Technical contributions. We propose an algorithm to construct a glyph codebook, a lookup table that maps a message into perturbed glyphs and ensures the perturbation is unobtrusive to our eyes. We then devise a recognition method that recovers the embedded message from an encoded document. Both the codebook construction and glyph recognition leverage CNNs. Additionally, we propose an error-correction coding scheme that rectifies recognition errors due to factors such as camera distortion. Built on a 1700-year old number theorem, the Chinese Remainder Theorem, and a probabilistic decoding model, our coding scheme is able to correct more errors than what block codes based on Hamming distance can correct, outperforming their theoretical error-correction upper bound.

2 RELATED WORK

We begin by clarifying a few typographic terminologies [Campbell and Kautz 2014]: the typeface of a character refers to a set of fonts each composed of glyphs that represent the specific design and features of the character. With this terminology, our method embeds messages by perturbing the glyphs of the fonts of text letters.

Font manipulation. While our method perturbs glyphs using the generative model by Campbell and Kautz [2014], other methods create fonts and glyphs with either computer-aided tools [Ruggles 1983] or automatic generation. The early system by [Knuth 1986] creates parametric fonts and was used to create most of the Computer Modern typeface family. Later Shamir and Rappoport [1998] proposed a system that generate fonts using high-level parametric features and constraints to adjust glyphs. This idea was extended to parameterize glyph shape components [Hu and Hersch 2001]. Other approaches generate fonts by deriving from examples and templates [Lau 2009; Suveeranont and Igarashi 2010]. More recent works have focused on structuring fonts based on similarity [Lovisch-cach 2010] or crowdsourced attributes [O’Donovan et al. 2014].

Font recognition. Automatic font recognition from a photo or image has been studied [Avilés-Cruz et al. 2005; Jung et al. 1999; Ramanathan et al. 2009]. These methods identify fonts by extracting statistical and/or typographical features of the document. Recently in [Chen et al. 2014], the authors proposed a scalable solution leveraging supervised learning. Then, Wang et al. [2015] improved font recognition using Convolutional Neural Networks. Their algorithm can run without resorting to character segmentation and optical character recognition methods. In our system, we use existing algorithms to recognize font texts of the input document, but further devise an algorithm to recognize glyph perturbation for recovering the embedded information. Unlike existing font recognition methods that identify fonts from a text of many letters, our algorithm aims to identify glyph perturbation for individual letters.

Text steganography. Our work is related to digital steganography (such as digital watermarks for copyright protection), which has been studied for decades, mostly focusing on videos, images, and audios. However, digital text steganography is much more challenging [Agarwal 2013], and thus much less developed. We categorize existing methods based on their features (see Table 1):

Methods based on cover text generation (CTG) hide a secret message by generating an ad-hoc cover text which looks lexically and syntactically convincing [Wayner 1992, 2009]. However, this type of steganography is unable to embed messages in existing text documents. Thus, they fail to meet the attribute that we call cover text preservation (CP), and have limited applications.

The second type of methods exploits format-specific features (FSF). For example, specifically for Microsoft Word document, Bhaya et al. [2013] assign each text character a different but visually similar font available in Word to conceal messages. Others hide messages by changing the character scale and color or adding underline styles in a document [Panda et al. 2015; Stojanov et al. 2014], although those changes are generally noticeable. More recent methods exploit special ASCII codes and Unicodes that are displayed as an empty space in a PDF viewer [Chaudhary et al. 2016; Rizzo et al. 2016]. These methods are not format independent (FI), they are bounded to a specific file format (such as Word or PDF) and text viewer. The concealed messages would be lost if the document was converted.
in a different format or even opened with a different version of the same viewer. If also fails to preserve the concealed message when the document is printed on paper (PP) and photographed later.

More relevant to our work is the family of methods that embed messages via what we call structural perturbations (SP). Line-shift methods [Alattar and Alattar 2004; Brassil et al. 1995] hide information by perturbing the space between text lines: reducing or increasing the space represents a 0 or 1 bit. Similarly, word-shift methods [Brassil et al. 1995; Kim et al. 2003] perturb the spaces between words. Others perturb the shape of specific characters, such as raising or dropping the positions of the dots above “i” and “j” [Brassil et al. 1995]. These methods cannot support fine granularity coding (FGC), in the sense that they encode 1 bit in every line break, word break or special character that appears sparsely. Our method provides fine granularity coding by embedding information in individual letters, and thereby has a much larger information capacity. In addition, all these methods demonstrate retrieval of hidden messages from digital document files only. It is unclear to what extent they can decode from real photos of text.

Table 1 summarizes related work and their main attributes. Like most of these work, our method aims to perturb the appearance of the text in an unobtrusive, albeit not fully imperceptible, way. But our method is advantageous by providing more desired attributes.

### 3 OVERVIEW

Our FontCode system embeds in a text document any type of information as a bit string. For example, an arbitrary text message can be coded into a bit string using the standard ASCII code or Unicode. We refer to such a bit string as a plain message.

In a text document, the basic elements of embedding a plain message are the letters, appearing in a particular font. Our idea is to perturb the glyph of each letter to embed a plain message. To this end, we leverage the concept of font manifold proposed by Campbell and Kautz [2014]. Taking as input a collection of existing font files, their method creates a low-dimensional font manifold.

| Category | Previous work | Attribute |
|----------|---------------|-----------|
| CTG      | [Agarwal 2013; Wayner 2009] | ✓ ✓ ✓ ✓ |
| SP       | [Alattar and Alattar 2004; Brassil et al. 1995; Gutub and Fattani 2003] | ✓ ✓ ✓ |
| FSF      | [Bhaya et al. 2013; Chaudhary et al. 2016; Panda et al. 2015; Rizzo et al. 2016] | ✓ ✓ |

**Our work** ✓ ✓ ✓ ✓ ✓

Table 1. A summary of related text steganographic methods. CP indicates cover text preservation; FGC indicates fine granularity coding; FI indicates format-independent; PP indicates printed paper.

3.1 Message Embedding

Our message embedding method consists of two steps, (i) precomputation of a codebook for processing all documents and (ii) runtime embedding of a plain message in a given document.

During precomputation, we construct a codebook of perturbed glyphs for typically used fonts. Consider a font such as Times New Roman. Each character in this font corresponds to a specific location, \( \bar{u} \), on the font manifold. We identify a set of locations on the manifold as the perturbed glyphs of \( \bar{u} \) and denote them as \( \{u_0, u_1, \ldots\} \) (see Fig. 2). Our goal in this step is to select the perturbed glyphs such that their differences from the glyph \( \bar{u} \) of the original font is almost unnoticeable to our naked eyes but recognizable to a computer algorithm (detailed in §4). The sets of perturbed glyphs for all characters with typically used fonts form our codebook.

At runtime, provided a text document (or a text region or paragraphs), we perturb the glyph of the letter in the document to embed a given plain message. Consider a letter in an original glyph \( \bar{u} \) in the given document. Suppose in the precomputed codebook, this letter has \( N \) perturbed glyphs, namely \( \{u_0, u_1, \ldots, u_{N-1}\} \). We embed in the letter an integer \( i \) in the range of \([0, N)\) by changing its glyph from \( \bar{u} \) to \( u_i \) (see Fig. 2-top). A key algorithmic component of this step is to determine the embedded integers for all letters such that together they encode the plain message.

In addition, we propose a new error-correcting coding scheme to encode the plain message. This coding scheme adds certain redundancy (i.e., some extra data) to the coded message, which, at decoding time, can be used to check for consistency of the coded message and recover it from errors (see §5).

3.2 Message Retrieval

To retrieve information from a coded text document, the first step is to recover an integer from each letter. For each letter in the document, suppose again this letter has \( N \) perturbed glyphs in the codebook, whose manifold locations are \( \{u_0, u_1, \ldots, u_{N-1}\} \). We recognize its glyph \( u' \) in the current document as one of the \( N \)

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1See the character set coding standards by the Internet Assigned Numbers Authority (http://www.iana.org/assignments/character-sets/character-sets.xhtml)
perturbed glyphs. We extract an integer $i$ if $u^i$ is recognized as $u_i$ (see Fig. 2-bottom). Our recognition algorithm works with not only vector graphics documents (such as those stored as PDFs) but also rasterized documents stored as pixel images. For the latter, the recognition leverages convolutional neural networks.

The retrieved integers are then fed into our error correction coding scheme to reconstruct the plain message. Because of the data redundancy, even if some glyphs are mistakenly recognized (e.g., due to poor image quality), those errors will be rectified and we will still be able to recover the message correctly (see §5).

4 GLYPH RECOGNITION

We start by focusing on our basic message embedding blocks: individual letters in a text document. Our goal in this section is to embed an integer number in a single letter by perturbing its glyph, and later retrieve that integer from a vector graphics or pixel image. We then preprocess the image. We crop the region of each letter using the classic algorithm by Otsu [1975]. This step helps to eliminate the influence caused by the variations of lighting conditions and background colors. Lastly, we resize the image region to have $200 \times 200$ pixels. This $200 \times 200$, black-and-white image for each letter is the input to our CNNs (Fig. 4-left).

4.2 Network Structure

We treat glyph recognition as an image classification problem: provided an image region of a letter which has a list of perturbed glyphs $\{u_0, u_1, \ldots\}$ in the codebook, our goal is to classify the input glyph of that letter as one from the list. Therefore, we train a CNN for each letter in a particular font.

Thanks to the image preprocessing, we propose to use a simple CNN structure (as illustrated in Fig. 4), which can be quickly trained and evaluated. The input is a $200 \times 200$, black-and-white image containing a letter. The CNN consists of three convolutional layers, each followed by a ReLU activation layer (i.e., $f : x \in \mathbb{R} \mapsto \max(0, x)$ and a $2 \times 2$ max pooling layer. The kernel size of the three convolutional layers are $8 \times 8 \times 32$, $5 \times 5 \times 64$, and $3 \times 3 \times 32$, respectively. The convolutional layers are connected with two fully connected (FC) layers, arranged in the following form (see Fig. 4):

$$\rightarrow \text{FC}(128) \rightarrow \text{Dropout} \rightarrow \text{FC}(N) \rightarrow \text{Softmax} \rightarrow \text{output}.$$  

Here "Dropout" indicates a 0.5-dropout layer, and FC($m$) is an $m$-dimensional FC layer. In the second FC layer, $N$ is the number of perturbed glyphs in the codebook for the letter in a certain font. After passing through a softmax layer, the output is an N-dimensional vector indicating the probabilities (or the inverse of "distance") of classifying the glyph of the input letter as one of the perturbed glyphs in the list. The glyph of the letter is recognized as $u_i$ if its corresponding probability in the output vector is the largest one.

4.3 Network Training

Training data. Our CNNs will be used for recognizing text document images that are either directly synthesized or captured by digital cameras. Correspondingly, the training data of the CNNs consist of synthetic images and real photos. Consider a letter whose perturbed glyphs from a standard font are $\{u_0, \ldots, u_{N-1}\}$. We print all the $N$ glyphs on a paper and take 10 photos with different lighting conditions and slightly different camera angle. While taking the

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photos, the camera is almost front facing the paper, mimicking the
scenarios of how the embedded information in a document would
can be read by a camera. In addition, we include synthetic images by
rasterizing each glyph (whose vector graphics path is generated
using [Campbell and Kautz 2014]) into a 200×200 image.

Data augmentation. To train the CNNs, each training iteration
randomly draws a certain number of images from the training data.
We ensure that half of the images are synthetic and the other half
are from real photos. To reduce overfitting and improve the ro-
VH: robustness, we augment the selected images before feeding them into
the training process. Each image is processed by the following
operations:

- Adding a small Gaussian noise with zero mean and standard
deviation 3.
- Applying a Gaussian blur whose standard deviation is uniformly
distributed between 0 (no blur) and 3px.
- Applying a randomly-parameterized perspective transformation.
- Adding a constant border with a width randomly chosen between
0 and 30px.

We note that similar data augmentations have been used in [Chen
et al. 2014; Wang et al. 2015] to enrich their training data. Lastly,
we apply the preprocessing routine described in §4.1, obtaining a
binary image whose pixel values are either 0 or 1.

Implementation details. In practice, our CNNs are optimized using
the Adam algorithm [Kingma and Ba 2015] with the parameters
β1 = 0.9, β2 = 0.999 and a mini-batch size of 15. The network was
trained with 105 update iterations at a learning rate of 10−3. Our
implementation also leverages existing libraries, Tensorflow [Abadi
et al. 2015] and Keras [Chollet et al. 2015].

4.4 Constructing The Glyph Codebook
The CNNs not only help to recognize glyphs at runtime, but also
enable us to systematically construct the glyph codebook, a lookup
table that includes a set of perturbed glyphs for every character in
commonly used fonts (such as Times New Roman, Helvetica, and
Calibri). Our codebook construction aims to satisfy three criteria: (i)
The included glyph perturbation must be perceptually similar; their
differences from the original fonts should be hardly noticeable to our
eyes. (ii) The CNNs must be able to distinguish the perturbed glyphs
reliably. (iii) Meanwhile, we wish to include as many perturbed
glyphs as possible in the codebook for each character, in order to
increase the capacity of embedding information (see §5).

To illustrate our algorithm, consider a single character in a given
font. We use its location ¯u on the character’s font manifold to refer
to the original glyph of the font. Our construction algorithm first
finds a large set of glyph candidates that are perceptually similar to
¯u. This step uses crowdsourced perceptual studies following a
standard user-study protocol. We therefore defer its details until
§6, while in this section we denote the resulting set of glyphs as C,
which typically has hundreds of glyphs. Next, we reduce the size of
C by discarding glyphs that may confuse our CNNs in recognition
tests. This is an iterative process, wherein each iteration takes the
following two steps (see Algorithm 1 in Appendix):

Confusion test. We randomly select M pairs of glyphs in C
(M =100 in practice). For each pair, we check if our CNN structure
(introduced in §4.2) can reliably distinguish the two glyphs. In this
case, we consider only the two glyphs, and thus the last FC layer
(recall §4.2) has two dimensions. We train this network with only
synthetic images processed by the data augmentations. We use
synthetic images generated by different augmentations to test the
accuracy of the resulting CNN. If the accuracy is less than 95%, then
we record this pair of glyphs in a set D.

Updating glyph candidate set. Next, we update the glyph can-
didates in C to avoid the recorded glyph pairs that may confuse the
CNNs while retaining as many glyph candidates as possible in C.
To this end, we construct a graph where every node i represents
a glyph in C. Initially, this graph is completely connected. Then,
the edge between node i and j is removed if the glyph pair i j is
listed in D, meaning that i and j are hardly distinguishable by our
CNN. With this graph, we find the maximum set of glyph that can
be distinguished from each other. This amounts to the classic max-
imum clique problem on graphs. Although the maximum clique
problem has been proven NP-hard (see page 97 of [Karp 1972]), our
graph size is small (with up to 200 nodes), and the edges are sparse.
Consequently, many existing algorithms suffice to find the maxi-
mum clique efficiently. In practice, we choose to use the method of
[Konc and Janezic 2007]. Lastly, the glyphs corresponding to the
maximum clique nodes form the updated glyph candidate set C, and
we move on to the next iteration.

This iterative process stops when there is no change of C. In our
experiments, this takes up to 5 iterations. Because only synthetic
images are used as training data, this process is fully automatic and
fast, but it narrows down the glyph candidates conservatively—two
glyphs in C might still be hardly distinguishable in real photos.
Therefore, in a last step, we train a CNN as described in §4.3 using
both synthetic images and real photos to verify if the CNN can

![Network Architecture](image)
reliably recognize all glyphs in \( \mathcal{C} \). Here the last FC layer of CNN has a dimension of \(|\mathcal{C}|\) (i.e., the size of \( \mathcal{C} \)). At this point, \(|\mathcal{C}|\) is small (typically around 25). Thus, the CNN can be easily trained. Afterwards, we evaluate the recognition accuracy of the CNN for each glyph in \( \mathcal{C} \), and discard the glyphs whose recognition accuracy is below 90%. The remaining glyphs in \( \mathcal{C} \) are added to the codebook as the perturbed glyphs of the character.

4.5 Embedding and Retrieving Integers

Embedding. Now we can embed integers into a text document in either vector graphic or pixel image format. First, we extract from the input document the text content and the layout of the letters. Our method also needs to know the original font \( \mathbf{u} \) of the text. This can be specified by the user or automatically obtained from the metadata of a vector graphic document (such as a PDF). If the document is provided as a pixel image, recent methods [Chen et al. 2014; Wang et al. 2015] can be used to recognize the text font.

In order to embed an integer \( i \) in a letter \( \mathbf{u} \), we look up its perturbed glyph list \( \{u_0, \ldots, u_{N-1}\} \) in the precomputed codebook, and generate the letter shaped by the glyph \( u_i \) [Campbell and Kautz 2014]. We then scale the glyph to fit it into the bounding box of the original letter (which is detected by the OCR library for pixel images), and use it to replace the original letter of the input document.

Retrieval. To retrieve integers from a pixel image, we extract the text content and identify regions of individual letters using the OCR tool. After we crop the regions of the letters, they are processed in parallel by the recognition algorithm: they are preprocessed as described in §4.1 and then fed into the CNNs. An integer \( i \) is extracted from a letter if the output vector from its CNN has the \( i \)-th element as the largest (recall §4.2).

If the input document is provided as a vector graphics image (e.g., as a PDF file), glyph recognition of a letter is straightforward. In our codec, we store the outlines of the perturbed glyphs as polylines. In the integer embedding stage, these polylines are scaled to replace the paths of the original glyphs. In the retrieval stage, we compute the “distance” between the letter’s glyph polylines, denoted as \( f \), in the document and every glyph \( u_i \) in the perturbed glyph list of the codebook: we first scale the polylines of \( u_i \) to match the bounding box of \( f \), and then compute the \( L_2 \) distance between the polylines vertices of \( u_i \) and \( f \). We recognize \( f \) as \( u_j \) (and thus extract the integer \( j \)) if the distance between \( f \) and \( u_j \) is the minimum.

5 ERROR CORRECTION CODING

After presenting the embedding and retrieval of integer values over individual letters, we now focus on a plain message represented as a bit string and describe our coding scheme that encodes the bit string into a series of integers, which will be in turn embedded in individual letters. We also introduce an error-correction decoding algorithm that decodes the bit string from a series of integers, even when some integers are incorrect.

Algorithms presented in this section are built on the coding theory for noise channels, founded by Shannon’s landmark work [Shannon 1948]. We refer the reader to the textbook [Lin and Costello 2004] for a comprehensive introduction. Here, we start with a brief introduction of traditional error-correcting codes, to point out their fundamental differences from our coding problem.

5.1 Challenges of the Coding Problem

The most common error-correction coding scheme is block coding, in which an information sequence is divided into blocks of \( k \) symbols each. We denote a block using a \( k \)-tuple, \( r = (r_1, r_2, \ldots, r_k) \). For example, a 128-bit binary string can be divided into 16 blocks of 8-bit binary strings. In this case, \( k = 8 \), and \( r_j \) is either 0 or 1. In general, \( r_j \) can vary in other ranges of discrete symbols. A fundamental requirement of error-correction coding is that (i) the number of possible symbols for each \( r_j \) must be the same, and (ii) this number must be a prime power \( p^m \), where \( p \) is a prime number and \( m \) is a positive integer. In abstract algebraic language, it requires the blocks to be in a Galois Field, \( GF(p^m) \). For example, the aforementioned 8-bit strings are in \( GF(2) \). Most of the current error-correction coding schemes (e.g., Reed-Solomon codes [Reed and Solomon 1960]) are built on the algebraic operations in the polynomial ring of \( GF(p^m) \). At encoding time, they transform \( k \)-tuple blocks into \( n \)-tuple blocks in the same Galois field \( GF(p^m) \), where \( n \) is larger than \( k \). At decoding time, some symbols in the \( n \)-tuple blocks can be incorrect. But as long as the total number of incorrect symbols in a block is no more than \( \left\lfloor \frac{n-k}{2}\right\rfloor \), regardless of the locations of incorrections, the coding scheme can fully recover the original \( k \)-tuple block.

In our problem, a text document consists of a sequence of letters. At first glance, we can divide the letter sequence into blocks of \( k \) letters each. Unfortunately, these blocks are ill-suited for traditional block coding schemes. For example, consider a five-letter block, \((C_1, C_2, \ldots, C_5)\), with an original font \( \mathbf{u} \). Every letter has a different capacity for embedding integers: in the codebook, \( C_1 \) has \( s_i \) glyphs, so it can embed integers in the range \([0, s_i]\). However, in order to use block coding, we need to find a prime power \( p^m \) that is no more than any \( s_i, i = 1 \ldots 5 \) (to construct a Galois field \( GF(p^m) \)). Then every letter can only embed \( p^m \) integers, which can be significantly smaller than \( s_i \). Perhaps a seemingly better approach is to find \( t_i = \left\lceil \log_{s_i} s_j \right\rceil \) for every \( s_i \), and use the \( 5 \)-letter block to represent a \( T \)-bit binary string, where \( T = \sum_{i=1}^{T} t_i \). In this case, this binary string is in \( GF(2) \), valid for block coding. Still, this approach wastes much of the letters’ embedding capacity. For example, if a letter has 30 perturbed glyphs, this approach can only embed integers in \([0, 16]\). As experimentally shown in §8.2, it significantly reduces the amount of information that can be embedded. In addition, traditional block coding method is often concerned with a noisy communication channel, where an error occurs at individual bits. In contrast, our recognition error occurs at individual letters. When the glyph of a letter is mistakenly recognized, a chunk of bits becomes incorrect, and the number of
We start our presentation by defining our coding problem formally. Where must be injective, so \( \phi \) and of the recognition errors, it is possible that no \( m \) from a letter’s glyph is incorrect, then the input \( \tilde{r} \) has the same distance to \( r \) (e.g., when \( r = r_b \), and \( r \) may be mistakenly decoded as \( r_1 \) (e.g., when \( r = r_c \)).

incorrect bits depends on specific letters. Thus, it is harder to set a proper relative redundancy (i.e., \((n - k)/n\) in block coding) to guarantee successful error correction.

5.2 Chinese Reminder Codes
To address these challenges, we introduce a new coding scheme based on a 1700-year-old number theory, the Chinese remainder theorem (CRT) [Katz and Imhausen 2007]. Error-correction coding based on Chinese remainder theorem has been studied in the field of theoretical computing [Boneh 2000; Goldreich et al. 1999], known as the Chinese Reminder Codes (CRC). Building on CRC, we propose a coding scheme offering improved error-correction ability (§5.3).

We start our presentation by defining our coding problem formally.

Problem definition. Given a text document, we divide its letter sequence into blocks of \( n \) letters each. Consider a block, denoted as \( \mathcal{C} = (C_1, C_2, ..., C_n) \) in an original font \( \tilde{u} \). Our goal for now is to embed an integer \( m \) in this \( n \)-letter block, where \( m \) is in the range \([0, M)\). We will map the plain message into a series of integers later in this section. Formally, we seek an encoding function \( \phi : m \rightarrow r \), where \( r = (r_1, ..., r_k) \) is an \( n \)-vector of integers. Following the coding theory terminology, we refer \( r \) as a codeword. The function \( \phi \) needs to ensure that every \( r_1 \) can be embedded in the letter \( C_i \). Meanwhile, \( \phi \) must be injective, so \( r_1 \) can be uniquely mapped to \( m \) through a decoding function \( \phi^*: r \rightarrow m \). Additionally, the composition of \( \phi \) and \( \phi^* \) must be fast, to encode and decode in a timely fashion.

5.2.1 Hamming Distance Decoding. We now introduce Hamming Distance decoding, a general decoding framework for block codes, to pave the way for our coding scheme.

Definition 5.1 (Hamming Distance). Given two codewords \( \mathbf{u} \) and \( \mathbf{v} \), the Hamming Distance \( H(\mathbf{u}, \mathbf{v}) \) measures the number of pair-wise elements in which they differ.

For example, given two codewords, \( \mathbf{u} = (2, 3, 1, 0, 6) \) and \( \mathbf{v} = (2, 0, 1, 0, 7) \), \( H(\mathbf{u}, \mathbf{v}) = 2 \).

Now we consider glyph recognition errors. If the integer retrieval from a letter’s glyph is incorrect, then the input \( \tilde{r} \) of the decoding function \( \phi^* \) may not be a valid codeword. In other words, because of the recognition errors, it is possible that no \( m \) satisfies \( \phi(m) = \tilde{r} \). To distinguish from a codeword, we refer to \( \tilde{r} \) as a code vector.

The Hamming distance decoding uses a decoding function \( \phi^* \) based on the Hamming distance: \( \phi^*(\tilde{r}) \) returns an integer \( m \) such that the Hamming distance \( H(\phi(m), \tilde{r}) \) is minimized over all \( m \in [0, M) \). Intuitively, although \( \tilde{r} \) may not be a valid codeword, we decode it as the integer whose codeword is closest to \( \tilde{r} \) under the measure of Hamming distance. Let \( H_m \) denote the minimum Hamming distance among all pairs of valid codewords, namely,

\[
H_m = \min_{i,j \in [0, M-1]} H(\phi(i), \phi(j)).
\]

The error-correction ability of Hamming distance decoding is bounded by the following theorem [Lin and Costello 2004].

Theorem 5.2. Let \( E \) denote the number of incorrect symbols in a code vector \( \tilde{r} \). Then, the Hamming distance decoding can correctly recover the integer \( m \) if \( E \leq \left\lfloor \frac{M-1}{2} \right\rfloor \); it can detect errors in \( \tilde{r} \) but not recover the integer correctly if \( \frac{H_m-1}{2} < E < H_m \).

An illustrative understanding of this theorem using an analogy of Euclidean distance is shown in Fig. 6. This theorem holds regardless of the encoding function \( \phi \), as long as it is a valid injective function.

5.2.2 Chinese Reminder Codes. We now introduce the following version of the Chinese Reminder Theorem, whose proof can be found in [Rosen 2011].

Theorem 5.3 (Chinese Reminder Theorem). Let \( p_1, p_2, ..., p_k \) denote positive integers which are mutually prime and \( M = \prod_{i=1}^{k} p_i \). Then, there exists an injective function,

\[
\phi : [0, M) \rightarrow [0, p_1] \times [0, p_2] \times ... \times [0, p_k),
\]

defined as \( \phi(m) = (r_1, r_2, ..., r_n) \), such that for all \( m \in [0, M) \), \( r_i = m \mod p_i \).

This theorem indicates that given \( k \) pairs of integers \( (r_1, p_1) \) with all \( p_i \) being mutually prime, there exists a unique non-negative integer \( m < \prod_{i=1}^{k} p_i \) satisfying \( r_i = m \mod p_i \) for all \( i = 1, ..., k \).

Indeed, \( m \) can be computed using the formula,

\[
m = CRT(r, p) = r_1 b_1 + \frac{p}{p_1} r_2 b_2 + ... + \frac{p}{p_n} r_n b_n, \tag{1}
\]

where \( P = \prod_{i=1}^{k} p_i \), and \( b_i \) is computed by solving a system of modular equations,

\[
b_i \frac{p}{p_i} \equiv 1 \pmod{p_i}, \quad i = 1, ..., k,
\]

using the classic Euclidean algorithm [Rosen 2011].

If we extend the list of \( p_i \) to \( n \) mutually prime numbers \( n > k \) such that the \( n - k \) additional numbers are all larger than \( p_i \) up to \( i = k \) (i.e., \( p_j > p_i \) for any \( j = k+1, ..., n \) and \( i = 1, ..., k \)), then we have an encoding function \( \phi \) for non-negative integer \( m < \prod_{i=1}^{k} p_i \):

\[
\phi(m) = (m \mod p_1, m \mod p_2, ..., m \mod p_n). \tag{2}
\]

This encoding function already adds redundancy: because \( m \) is smaller than the product of any \( k \) numbers chosen from \( p_i \), we can compute \( m \) from any \( k \) of the \( n \) pairs of \((r_i, p_i)\), according to the Chinese Reminder Theorem. Indeed, as proved in [Goldreich et al. 1999], the minimum Hamming distance of the encoding function (2)
for all $0 \leq m < \prod_{i=1}^{C} p_i$ is $n - k + 1$. Thus, the Hamming decoding function of $\phi$ can correct up to $\left\lfloor \frac{n - k}{2} \right\rfloor$ errors by Theorem 5.2.

**Encoding.** We now describe our encoding algorithm based on the encoding function $\phi(m)$ in (2).

- **Computing $p_i$.** Suppose that the letter sequence of a document has been divided into $N$ blocks, denoted as $C_1, ..., C_N$, each with $n$ letters. Consider a block $C_t = (C_1, ..., C_n)$, where $C_t$ indicates a letter with its original font $u_i$, whose integer embedding capacity is $s_i$ (i.e., $C_t$’s font $u_i$ has $s_i$ perturbed glyphs in the codebook). We depth-first search $n$ mutually prime numbers $p_i, i = 1 ..., n$, such that $p_i \leq s_i$ and the product of $k$ minimal $p_i$ is maximized. At the end, we obtain $p_i, i = 1 ... n$ and the product of $k$ minimal $p_i$ denoted as $M_t$ for each block $C_t$. Note that if we could not find mutually prime numbers $p_i$ for block $C_t$, we simply ignore the letter whose embedding capacity is smallest among all $s_i$ and include $C_{n+1}$ to this block. We repeat this process until we find a valid set of mutually prime numbers.

- **Determining $m_t$.** Given the plain message represented as a bit string $m$, we now split the bits into a sequence of chunks, each of which is converted into an integer and assigned to a block $C_t$. We assign to each block $C_t$ an integer $m_t$ with $\lceil \log_2 M_t \rceil$ bits, which is sequentially cut from the bit string $m$ (see Fig. 7).

- **Embedding.** For every block $C_t$, we compute the codeword using the CRT encoding function (2), obtaining $r = (r_1, ..., r_n)$. Each $r_i$ is then embedded in the glyph of the letter $C_t$ in the block $C_t$ as described in §4.5.

**Decoding.** At decoding time, we recognize the glyphs of the letters in a document and extract integers from them, as detailed in §4.5. Next, we divide the letter sequence into blocks, and repeat the algorithm of computing $p_i$ and $M_t$ as in the encoding step, for every block. Given a block $C_t$, the extracted integers from its letters form a code vector $\tilde{r}_t = (\tilde{r}_1, ..., \tilde{r}_n)$. We refer to it as a code vector because some of the $\tilde{r}_i$ may be incorrectly recognized. To decode $r_t$, we first compute $\tilde{m}_t = \text{CRT}(\tilde{r}_t, p_t)$ where $p_t$ stacks all $p_i$ in the block. If $\tilde{m}_t < M_t$, then $\tilde{m}_t$ is the decoding result $\phi^*(\tilde{r}_t)$, because the Hamming distance $H(\phi(m_t), \tilde{r}) = 0$. Otherwise, we decode $\tilde{r}_t$ using the Hamming decoding function: concretely, since we know the current block can encode an integer in the range $[0, M_t]$, we decode $\tilde{r}_t$ into the integer $m_t$ by finding

$$m_t = \phi^*(\tilde{r}_t) = \min_{m \in [0, M_t]} H(\phi(m), \tilde{r}).$$

As discussed above, this decoding function can correct up to $\left\lfloor \frac{n - k}{2} \right\rfloor$ incorrectly recognized glyphs in each block. Lastly, we convert $m_t$ into a bit string and concatenate $m_t$ from all blocks sequentially to recover the plain message.

**Implementation details.** A few implementation details are worth noting. First, often times letters in a document can carry a bit string much longer than the given plain message. To indicate the end of the message, we attach a special chunk of bits (end-of-message bits) at the end of each plain message, very much akin to the end-of-line (newline) character used in digital text systems. Second, in practice, blocks should be relatively short (i.e., $n$ is small). If $n$ is large, it becomes much harder to find $n$ mutually prime numbers that are no more than each letter’s embedding capacity. In practice, we choose $n = 5$ and $k = 3$ which allows one mistaken letter in every 5-letter block. The small $n$ and $k$ also enable brute-force search of $m_t$ in (3) sufficiently fast, although there also exists a method solving (3) in polynomial time [Boneh 2000; Goldreich et al. 1999].

5.3 Improved Error Correction Capability

Using the Chinese Remainder Codes, the error-correction capacity is upper bounded. Theorem 5.2 indicates that at most $\left\lfloor \frac{n - k}{2} \right\rfloor$ mistakenly recognized glyphs are allowed in every letter block. We now break this theoretical upper bound to further improve our error-correction ability, by exploiting specific properties of our coding problem. To this end, we propose a new algorithm based on the maximum likelihood decoding [Lin and Costello 2004].

In coding theory, maximum likelihood decoding is not an algorithm. Rather, it is a decoding philosophy, a framework that models the decoding process from a probabilistic rather than an algebraic point of view. Consider a letter block $C$ and the code vector $\tilde{r}$ formed by the extracted integers from $C$. We treat the true codeword $r$ encoded by $C$ as a latent variable (in statistic language), and model the probability of $r$ given the extracted code vector $\tilde{r}$, namely $\mathbb{P}(r|\tilde{r})$. With this likelihood model, our decoding process finds a codeword $\hat{r}$ that maximizes the probability $\mathbb{P}(r|\hat{r})$, and decodes $r$ into an integer using the Chinese Remainder Theorem formula (1).

When there are at most $\left\lfloor \frac{n - k}{2} \right\rfloor$ errors in a block, the Hamming decoding function (3) is able to decode. In fact, it can be proved that when the number of errors is under this bound, there exists a unique $m \in [0, M_t]$ that minimizes $H(\phi(m), \tilde{r})$ [Lin and Costello 2004], and that when the number of errors becomes $\left\lfloor \frac{n - k}{2} \right\rfloor + 1$, there may be multiple $m \in [0, M_t]$ reaching the minimum (see Fig. 6 for an intuitive explanation). The key idea of breaking this bound is to use a likelihood model to choose an $m$ when ambiguity occurs for the Hamming decoding function (3).

Consider a block with $\left\lfloor \frac{n - k}{2} \right\rfloor + 1$ errors, and suppose in (3) we find $N$ different integers $m_i$, all of which lead to the same minimal Hamming distance to the code vector $\tilde{r}$. Let $r_i = \phi(m_i), i = 1 ... N$, denote the corresponding codewords. We use another subscript $j$ to index the integer elements in code vectors and codewords. For every $r_i$, some of its integer elements $r_{ij}$ differs from the corresponding integer elements $\tilde{r}_j$. Here $r_{ij}$ can be interpreted as the index of the perturbed glyphs of the $j$-th letter. We denote this glyph as $u_{ij}$ and the
The task is to select the most similar font pair from the two pairs of font images. The two images on the left column are always identical fonts.

Your task is to select the most similar font pair from
the two pairs of font images. 
The two images on the left column are always identical fonts.

Instructions:
Your task is to select the most similar font pair from the two pairs of font images. 
The two images on the left column are always identical fonts.

Question 1

Fig. 9. MTurk user interface.

Analysis. From the raters’ response, we estimate a scalar value $s_i = s(u_i; \tilde{u})$, the perceptual similarity value of the glyph $u_i$ to the original glyph $\tilde{u}$, for every glyph $u_i \in F$. Let a set of tuples $D = \{(u_i, u_j, u, q)\}$ record the user study responses, where $u_i$ and $u_j$ are randomly selected glyphs being compared, $u$ is the MTurk rater’s ID, and the binary value $q$ is the rater’s choice: $q = 1$ indicates the rater judges $u_i$ perceptually closer to $\tilde{u}$, and $q = 0$ otherwise. We model the likelihood of the rater’s choice using a logistic function,

$$p(q = 1 | u_i, u_j, u) = \frac{1}{1 + \exp \left( \tau_u (s_{ij} - s_j) \right)}.$$  

where the scalar $\tau_u$ indicates the rater’s reliability. With this model, all the similarity values $s_i$ and user reliability values $\tau_u$ are obtained by minimizing a negative log-likelihood objective function,

$$E(s, r) = -\sum_k \left[ q^k \ln p(q = 1 | u_i^k, u_j^k, u^k) + (1 - q^k) \ln p(q = 0 | u_i^k, u_j^k, u^k) \right],$$

where $k$ indices the MTurk response in $D$, $r$ stacks the raters’ reliability values, and $s$ stacks the similarity values for all $u_j \in F$. The $s_j$ values are then normalized in the range of $[0, 1]$.

We learn the similarity values for the glyphs of every character with a font $\tilde{u}$ independently. Fig. 8 visualizes the perceptual similarity of glyphs near the standard Times New Roman for the character “a”. Lastly, We iterate through all the pre-sampled glyphs $u_j \in F$, and add those whose similarity value $s_j$ is larger than a threshold
(0.85 in practice) into a set C, forming the set of perceptually similar glyphs for constructing the codebook (in §4.4).

7 APPLICATIONS

Our method finds many applications. In this section, we discuss four of them, while referring to the supplemental video for their demonstrations and to §8.1 for implementation summaries.

7.1 Application I: Format-Independent Metadata

Many digital productions carry metadata that provide additional information, resources, and digital identification [Greenberg 2005]. Perhaps most well-known is the metadata embedded in photographs, providing information such as camera parameters and copyright. PDF files can also contain metadata2. In fact, metadata has been widely used by numerous tools to edit and organize digital files.

Currently, the storage of metadata is ad hoc, depending on specific file format. For instance, a JPEG image stores metadata in its EXIF header, while an Adobe PDF stores its metadata in XML format with Adobe’s XMP framework [Adobe 2001]. Consequently, metadata is lost whenever one converts an image from JPEG to PNG format, or rasterizes a vector graphics image into a pixel image. Although it is possible to develop a careful converter that painstakingly preserves the metadata across all file formats, the metadata is still lost whenever the image or document is printed on paper.

Our FontCode technique can serve as a means to host text document metadata. More remarkably, the metadata storage in our technique is format-independent, because format conversion and rasterization of text documents, as well as printing on paper, all preserve the glyphs of letters. Once information is embedded in a document, one can freely convert it to a different file format, or rasterize it into a pixel image (as long as the image is not severely downsampled), or print it on a piece of paper. Throughout, the metadata is retained (see video).

7.2 Application II: Imperceptible Optical Codes

Our FontCode technique can also be used as optical barcodes embedded in a text document, akin to QR codes [Denso 2011]. Barcodes have numerous applications in advertising, sales, inventory tracking, robotics, augmented reality, and so forth. Similar to QR codes that embed certain level of redundancy to correct decoding error, FontCode also supports error-correction decoding. However, all existing barcodes require to print black-and-white blocks and bars, which can be visually distracting and aesthetically imperfect. Our technique, in contrast, enables not only an optical code but an unobtrusive optical code, as it only introduces subtle changes to the text appearance. Our retrieval algorithm is sufficiently fast to provide point-and-shoot kind of message decoding. It can be particularly suitable for use as a replacement of QR codes in an artistic work such as a poster or flyer design, where visual distraction needs to be minimized. As a demonstration, we have implemented an iPhone application to read coded text (see video).

7.3 Application III: Encrypted Message Embedding

Our technique can further encrypt a message when embedding it in a document, even if the entire embedding and retrieval algorithms are made public. Recall that when embedding an integer i in a letter c of a glyph u, we replace u with a glyph chosen from a list of perturbed glyphs in the codebook. Let \( \mathcal{L}_c = \{u_0, \ldots, u_{N-1}\} \) denote this list. Even though the perturbed glyphs for every character in a particular font are precomputed, the order of the glyphs in each list \( \mathcal{L}_c \) can be arbitrarily user-specified. The particular orders of all \( \mathcal{L}_c \) together can serve as an encryption key.

For example, when Alice and Bob3 communicate through encoded documents, they can use a publicly available codebook, but agree on a private key, which specifies the glyph permutation of each list \( \mathcal{L}_c \). If an original list \( \{u_0, u_1, u_2, \ldots\} \) of a letter is permuted into \( \{u_{p_0}, u_{p_1}, u_{p_2}, \ldots\} \) by the key, then Alice uses the glyph \( u_{p_i} \), rather than \( u_i \), to embed an integer i in the letter, and Bob deciphers the message using the same permuted codebook. For a codebook that we precomputed for Times New Roman (see the supplemental document), if we only consider lowercase English alphabet, there exist \( 1.39 \times 10^{452} \) different keys (which amount to a 837-bit key); if we also include uppercase English alphabet, there exist \( 5.73 \times 10^{442} \) keys (which amount to a 1470-bit key). Thus, without resorting to any existing cryptographic algorithm, our method already offers a basic encryption scheme. Even if others can carefully examine the text glyphs and discover that a document is indeed embedding a message, the message can still be protected from leaking.

7.4 Application IV: Text Document Signature

Leveraging existing cryptographic techniques, we augment FontCode to propose a new digital signature technique, one that can authenticate the source of a text document and guarantee its integrity (thereby protecting from tampering). This technique has two variations, working as follows:

**Scheme 1.** When Alice creates a digital document, she maps the document content (e.g., including letters, digits, and punctuation) into a bit string through a cryptographic hash function such as the MD5 [Rivest 1992] and SHA [Eastlake and Jones 2001]. We call this bit string the document’s hash string. Alice then chooses a private key to permute the codebook as described in §7.3, and uses the permuted codebook to embed the hash string into her document. When Bob tries to tamper this document, any change leads to a different hash string. Without knowing Alice’s private key, he cannot embed the new hash string in the document, and thus cannot tamper the document successfully. Later, Alice can check the integrity of her document, by extracting the embedded hash string and comparing it against the hash string of the current document.

**Scheme 2.** The above algorithm allows only Alice to check the integrity of her document, as only she knows her private key. By combining with asymmetric cryptography such as the RSA algorithm [Rivest et al. 1978], we allow everyone to check the integrity of a document but not to tamper it. Now, the codebook is public but

2If you are reading this paper with Adobe Acrobat Reader, you can view its metadata by choosing File→Properties and clicking the ‘Additional Metadata’ under the ‘Description’ tab.

3Here we follow the convention in cryptography, using Alice and Bob as placeholder names for the convenience of presenting algorithms.
not permuted. After Alice generates the hash string of her document, she encrypts the hash string using her private key by an asymmetric cryptosystem, and obtains an encrypted string. Then, she embeds the encrypted string in the document using the FontCode method, while making her public key available to everyone. In this case, Bob cannot tamper the document, as he does not have Alice’s private key to encrypt the hash string of an altered document. But everyone in the world can extract the encrypted string using the FontCode method, and decipher the hash string using Alice’s public key. If the deciphered hash string matches the hash string of the current document, it proves that (i) the document is indeed sourced from Alice, and (ii) the document has not been modified by others.

Advantages. In comparison to existing digital signatures such as those in Adobe PDFs, our method is format-independent. In contrast to PDF files whose signatures are lost when the files are rasterized or printed on physical papers, our FontCode signature is preserved regardless of file format conversion, rasterization, and physical printing.

Further extension. In digital text forensics, it is often desired to not only detect tampering but also locate where in the text the tampering occurs. In this regard, our method can be extended for more detailed tampering detection. As shown in our analysis (§8.2), in a typical English document, we only need about 80 letters to embed (with error correction) a string of 128 bits, which is the length of a hash string resulted from a typical cryptographic hash function (e.g., MD5). Given a document, we divide its text into a set of segments, each with at least 80 letters. We then compute a hash string for each segment and embed the encrypted strings in individual segments. This creates a fine granularity of text signatures, allowing the user to check which text segment is modified, and thereby locating tampering occurrences more precisely. For example, in the current text format of this paper, every two-column line consists of around 100 letters, meaning that our method can identify tampering locations up to two-column lines in this paper. To our knowledge, digital text protection with such a fine granularity has not been realized.

Discussion about the storage. We close this section with a remark on the memory footprint of our steganographic documents. If a document is stored as a pixel image, then it consumes no additional memory. If it is in vector graphics format, our current implementation stores the glyph contour polylines of all letters. A document with 376 letters with 639 bits encoded will consume 1.2M memory in a compressed SVG form and 371K in a compressed JPEG format. PDF files can embed glyph shapes in the file and refer to those glyphs in the text. Using this feature, we can also embed the entire codebook in a PDF, introducing about 1.3M storage overhead, regardless of the text length. In the future, if all glyphs in the codebook are pre-installed on the operating system, like the current standardized fonts, the memory footprint of vector graphic documents can be further reduced.

8 RESULTS AND VALIDATION
We now present the results and experiments to analyze the performance of our technique and validate our algorithmic choices. Here we consider text documents with English alphabet, including both

Pippin looked out from the shelter of Gandalf’s cloak. He wondered if he was awake or still sleeping still in the swift moving dream in which he had been wrapped so long since the great ride began. The dark world was rushing by and the wind sang loudly in his ears. He could see nothing but the wheeling stars away to his right vast shadows against the sky where the mountains of the South marched.

lower- and upper-case letters, while the exact method can be directly applied to digits and other special characters. We first present our main results (§8.1), followed by the numerical (§8.2) and perceptual (§8.3) evaluation of our method.

8.1 Main Results
We implemented the core coding scheme on a Intel Xeon E5-1620 8 core 3.60GHz CPU with 32GB of memory. The CNNs are trained with an Nvidia Geforce TITAN X GPU. Please see our accompanying video for the main results. A side-by-side comparison of an original document with a coded document is shown in Fig. 10.

Metadata viewer. We implemented a simple text document viewer that loads a coded document in vector graphics or pixel image format. The viewer displays the document. Meanwhile, it extracts the embedded metadata with our decoding algorithm and presents it in a side panel.

Unobtrusive optical codes. We also implemented an iPhone application (see Fig. 1), by which the user can take a photo of an encoded text displayed on a computer screen or printed on paper. The iPhone application interface allows the user to select a text region to capture. The captured image is sent through the network to a decoding server, which recovers the embedded message and sends it back to the smartphone.

Embedding encrypted message. Our implementation allows the user to load an encryption key file that specifies the permutation for all the lists of perturbed glyphs in the codebook. The permutation can be manually edited, or randomly generated—given a glyph list of length n, one can randomly sample a permutation from the permutation group S_n [Seress 2003] and attach it to the key.

Text document signature. We use our technique to generate a MD5 signature as described in §7. Since the MD5 checksum has only 128 bits, we always embed it in letters from the beginning of the text. Our text document viewer can check the signature and alert the user if the document shows as tampered.

Fig. 10. (top) an input text document. (bottom) the output document that embeds a randomly generated message.
8.2 Validation

Information capacity. As described in §5, we use \( n = 5 \) and \( k = 3 \) in our error-correction coding scheme. In every 5-letter block, if the mutually prime numbers are \( p_i, i = 1...5 \), then this block can encode \( \prod_{i=1}^{5} p_i \) bits of information. To estimate the information capacity of our scheme for English text, we randomly sample 5 characters from the alphabet to form a block. The characters are sampled based on the widely known English letter frequencies (e.g., “e” is the most frequently used while “z” is the least used) [Ferguson and Schneier 2003]. We compute the average number of bits that can be encoded by a character. The result is 1.77, suggesting that on average we need 73 letters to encode a 128-bit MD5 checksum for the application of digital signature (§7).

Next, we compare our coding scheme with the simple approach discussed in §5.1. Recall that our method can correct at least one error in a block of 5 letters, which amounts to correcting \( \log_2(\max s_j) \) bits out of the total \( \sum_{j=1}^{5} \log_2 s_j \) bits. The simple approach in §5.1 can store \( \sum_{j=1}^{5} \log_2 s_j \) bits of information. But in order to correct one recognition error of the letter with the standard linear block codes, it needs to spend \( 2 \log_2(\max s_j) \) bits for adding redundancy, leaving \( \sum_{j=1}^{5} \log_2 s_j - 2 \log_2(\max s_j) \) bits to store information. We compare it with our method using The Lord of The Rings, Chapter 1 as our input text, which contains in total 41682 useful letters (9851 words). As shown in the adjacent figure, as the number of letters increases, our method can embed significantly more information.

Decoding accuracy. We first evaluate the glyph recognition accuracy of our CNNs. For every character, we print it repeatedly on a paper with randomly chosen glyphs from the codebook and take five photos under different lighting conditions. Each photo has regions of around 220px×220px containing a character. We use these photos to test CNN recognition accuracy, and for all characters, the accuracy is above 90%.

We also evaluate the decoding accuracy of our method. We observed that decoding errors are mainly caused by image rasterization. If the input document is in vector graphics format, the decoding result is fully accurate, as we know the glyph outlines precisely. Thus, we evaluate the decoding accuracy with pixel images. We again use The Lord of The Rings, Chapter 1 to encode a random bit string. We rasterize the resulting document into images with different resolutions, and measure how many letters and blocks can be decoded correctly. Fig. 11-left shows the testing result.

We also theoretically estimate the decoding robustness of our maximum likelihood decoding method (§5.3). Suppose the probability of correctly recognizing the glyph of a single letter is a constant \( P_1 \). The probability \( P_2 \) of correctly decoding a single 5-letter block can be derived analytically: if we only use Chinese Remainder Decoding algorithm (§5.2), \( P_2 \) is \( \left( \frac{1}{5} \right)^5 P_1 (1 - P_1) \). With the maximum likelihood decoding (§5.3), \( P_2 \) becomes \( \left( \frac{3}{5} \right)^5 P_1 (1 - P_1)^2 \). The improvement is visualized in Fig. 11-right.

Performance. We use tensorflow [Abadi et al. 2015] with GPU support to train and decode the input. It takes 0.89 seconds to decode a text sequence with 176 letters (30 blocks). Our encoding algorithm is running in a single thread CPU, taking 7.28 seconds for the same length of letters.

Error correction improvement. In §5.3, we hypothesize that the probability of recognizing an input pixel glyph \( f \) as a glyph \( u \) in the codebook is proportional to the softmax output of the CNNs. We validated this hypothesis experimentally. Here we denote the softmax output value for recognizing \( f \) as a perturbed glyph \( u^* \), the probability values \( g(u, f) \) and \( g(u^*, f) \) are both high (although \( d(u, f) \) is higher) and close to each other, indicating that \( f \) may be recognized as \( u \) or \( u^* \) with close probabilities. Thus, we conclude that using a likelihood model proportional to \( g(u^*, f) \) is reasonable.

Fig. 11. (left) The accuracy of our CNN decoder changes as the resolution in height of the letters increases. (right) Theoretical improvement of maximum likelihood decoding (green) over the Chinese Remainder coding (orange).

Fig. 12. Decoding Probability. (top) A small region of photo to be decoded, where red boxes indicate recognition errors. (bottom) Each row visualizes the probabilities of recognizing input glyphs (from the image) as the perturbed glyphs. Along the x-axis, every bar corresponds to a perturbed glyph in the codebook. The values on the y-axis are the output from our CNNs. When an error occurs, the blue and red bars indicate the discrepancy between the correctly and incorrectly recognized glyphs.
Additionally, we extensively tested our decoding algorithm on photos of text documents, and verified that it can successfully decode all 5-letter blocks that have at most 2 errors. A small snapshot of our tests is shown in Fig. 13.

### 8.3 Perceptual Evaluation

To evaluate the subjective distortion introduced by perturbing the glyphs of a document, we conducted two user studies on MTurk. Both studies follow the standard 2AFC protocol which is described in §6 and has been used in other contexts.

Study A assesses the perceptual distortion of a perturbed glyph with respect to a standard font. We prepare a set of paragraphs, and the glyphs of each paragraph are from one of the six categories: (1) the standard Times New Roman; (2-5) the perturbed glyphs from four glyph codebooks, in which the thresholds used to select the perceptually similar glyph candidates are 0.95, 0.85 (i.e., the value we use in §6), 0.75, and 0.65, respectively; and (6) a different font (Helvetica). The font size of each paragraph ranges from 25pt to 60pt, so the number of letters in the paragraphs varies. In each 2AFC question, we present the MTurk rater three short paragraphs: one is in standard Times New Roman, the other two are randomly chosen from two of the six categories. We ask the rater to select from the latter two paragraphs the one whose font is closest to standard Times New Roman (shown in the first paragraph). We assign 16 questions of this type to each rater, and there were 135 participants. An example question is included in the supplemental document.

After collecting the response, we use the same model (6) to quantify the perceptual difference of the paragraphs in each of the six categories with respect to the one in standard Times New Roman. In this case, $s_i$ in Eq. (6) is the perceptual difference of a category of paragraphs to the paragraphs in standard Times New Roman. As shown in Fig. 14, the results suggest that the glyphs in our codebook (generated with a threshold of 0.85) lead to paragraphs that are perceptually close to the paragraphs in original glyphs—much closer than the glyphs selected by a lower threshold but almost as close as the glyphs selected by a higher threshold (i.e., 0.95).

Study B assesses how much the use of perturbed glyphs in a paragraph affects the aesthetics of its typeface. We prepare a set of paragraphs whose glyphs are from one of the 12 categories: We consider four different fonts (see Fig. 15). For each font, we generate the glyphs in three ways, including (1) the unperturbed standard glyph; (2) the perturbed glyphs from our codebook using a perceptual threshold of 0.85; and (3) the perturbed glyphs from a codebook using a threshold of 0.7. In each 2AFC question, we present the MTurk rater two short paragraphs randomly chosen from two of the 12 categories, and ask the rater to select the paragraph whose typeface is aesthetically more pleasing to them. We assign 16 questions of this type to each rater, and there were 135 participants. An example question is also included in the supplemental document.

Again, using the logistic model (6), we quantify the aesthetics of the typeface for paragraphs in the aforementioned three categories of glyphs. Fig. 15 shows the results, indicating that, while the aesthetics are different across the four fonts, for each font paragraphs using glyphs from our codebook (a threshold of 0.85) are aesthetically comparable to the paragraphs in standard glyphs, whereas using glyphs selected by a lower perceptual threshold significantly depreciates the typeface aesthetics.

We note that in order to identify untrustworthy raters, in both user studies we include four control questions in each task assigned to the raters, in a way similar to those described in §6.

### 9 Conclusion and Future Work

We have introduced a new technique for embedding additional information in text documents. Provided a user-specified message, our method assigns each text letter an integer and embeds the integer by perturbing the glyph of each letter according to a precomputed codebook. Our method is able to correct a certain number of errors in the decoding stage, through a new error-correction coding scheme built on two algorithmic components: the Chinese Remainder coding and the maximum likelihood decoding. We have demonstrated our method with four applications, including text document metadata storage, unobtrusive optical codes on text, symmetric-key encryption, and format-independent digital signatures.

Currently we only consider standard fonts such as regular Times New Roman but not their variants such as Times New Roman Bold Italic. We can treat those variants separately and include their
perturbed glyphs in the codebook. Then, our method will work with those font variants.

When extracting messages from a rasterized text document, we rely on the OCR library to detect and recognize the characters, but we cannot recover any OCR detection error. If a character is mistakenly recognized by the OCR, the integer embedded in that character is lost, and our error-correction decoding may not be able to recover the plain message since different characters have different embedding capacities. However, in our experiments, the OCR library always recognizes characters correctly.

If a part of the text is completely occluded from the camera, our decoding algorithm will fail, as it needs to know how the text is split into blocks. In the future, we hope to improve our coding scheme so that it is able to recover from missing letters in the text as well.

In general, the idea of perturbing the glyphs for embedding messages can be applied to any symbolic system, such as other languages, mathematical equations, and music notes. It would be interesting to explore similar embedding methods and their applications for different languages and symbols.

Lastly, while our method is robust to format conversion, rasterization, as well as photograph and scan of printed papers, it suffers from the same drawback that almost all text steganographic methods have: if a text document is completely retyped, the embedded information is destroyed.

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ALGORITHM 1: Confusion Test

Initialize glyph candidates $C$;  
$G \leftarrow$ A complete graph whose nodes represent the elements of $C$; 
while true do  
    $Q \leftarrow$ Random select $M$ different pairs of nodes from $C$;  
    foreach pair $(u_i, u_j)$ in $Q$ do  
        $a \leftarrow$ Training accuracy of CNN described using $(u_i, u_j)$;  
        if $a < 0.95$ then  
            remove edge $(u_i, u_j)$ from $G$;  
        end  
    end  
    $G \leftarrow$ Maximum Clique($G$);  
    $C \leftarrow$ glyphs corresponding to nodes in $G$;  
    if No change to $C$ then  
        break;  
    end  
    end  
Train CNN using all elements in $C$;  
Remove elements whose recognition test accuracy is lower than 0.9;  
return $C$;  

ALGORITHM 2: Decoding

Input: code vector $\vec{r} = (\vec{r}_1, \ldots, \vec{r}_n)$, mutually prime integers $p = (p_1, \ldots, p_n)$, and $M$  
Output: Decoded integer $m$
 $\tilde{m} \leftarrow$ CRT($\vec{r}$, $p$);  
if $\tilde{m} < M$ then  
    $m \leftarrow \tilde{m}$;  
    return success;  
else  
    Find codeword $\hat{r}$, where $\hat{r} = \min_{\vec{r}} H(\vec{r}, \vec{r})$;  
    if $\hat{r}$ is not unique then  
        return fail;  
    else  
        $m \leftarrow$ CRT($\hat{r}$, $p$);  
        return success;  
    end  
end

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