IoTSign: Protecting Privacy and Authenticity of IoT using Discrete Cosine Based Steganography

Alsharif Abuadbba, Ayman Ibaida, and Ibrahim Khalil

Abstract—Remotely generated data by Intent of Things (IoT) has recently had a lot of attention for their huge benefits such as efficient monitoring and risk reduction. The transmitted streams usually consist of periodical streams (e.g. activities) and highly private information (e.g. IDs). Despite the obvious benefits, the concerns are the secrecy and the originality of the transferred data. Surprisingly, although these concerns have been well studied for static data, they have received only limited attention for streaming data. Therefore, this paper introduces a new steganographic mechanism that provides (1) robust privacy protection of secret information by concealing them arbitrarily in the transported readings employing a random key, and (2) permanent proof of originality for the normal streams. This model surpasses our previous works by employing the Discrete Cosine Transform to expand the hiding capacity and reduce complexity. The resultant distortion has been accurately measured at all stages - the original, the stego, and the recovered forms - using a well-known measurement matrix called Percentage Residual Difference (PRD). After thorough experiments on three types of streams (i.e. chemical, environmental and smart homes), it has been proven that the original streams have not been affected (< 1 %). Also, the mathematical analysis shows that the model has much lighter (i.e. linear) computational complexity $O(n)$ compared to existing work.

Index Terms—Steganography, Discrete Cosine, Privacy Preservation, Authenticity, IoT

I. INTRODUCTION

Lately, enormous interest has been expressed in gathering data remotely to effectively monitor various activities such as climate change, border invasion, battlefield scenarios, nuclear facilities or traffic screening. The streams are collected wirelessly using small sensors called Internet of Things (IoT) and forwarded to their final destination (e.g. operation centers). The continuous streams usually contain two types of data: (1) normal samples (e.g. activity data) and (2) extremely secret information (e.g. nuclear facility or border screen geometric location, facility IDs and small pictures of the locations coupled with date and time). Despite the apparent advantages of these activities, they create various concerns for the privacy of the secret information and the authenticity of the ordinary readings (See Fig. 1). Surprisingly, while these concerns have been well studied for static data, they have received limited attention for streaming data.

The reasons for this are (1) the generators of these streams (i.e. remote IoT) pose unique challenges (e.g. their presence in an uncontrollable environment, resource constraints such as memory and power, and topological constraints where the data should go through multiple public hops to the final destination) which prevent a direct transplant of existing privacy protection and authenticity techniques; (2) the massive size of these streams force the operation centers to do offshore operations (e.g. using cloud servers).

To overcome the identified privacy and authenticity concerns, simple encryption-based techniques using symmetric and asymmetric keys and digital signature have been proposed. However, their main limitation is that machine learning techniques and mathematical operations cannot be applied directly to the encrypted form (i.e. cipher-text) which leads to revealing the keys to the intermediate hops and cloud providers to efficiently work on the data (i.e. the confidentiality issue).

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Fig. 1. Notable issues arise when periodically collected readings by remote IoT should be directly sent to cloud-based servers for analysis.
the privacy of the secret information and the authenticity of the ordinary readings. In fact, their concerns are slightly different where the random perturbation is efficient in a scenario of a central data collector gathers and mines data from multiple providers, whereas K-anonymity is mainly used to obfuscate published data [8].

Therefore, researchers are obliged to look for new solutions to do the following tasks. (1) Provide solid privacy protection for the remotely collected secret data (e.g. geometric location, location picture, IDs and time). (2) Provide permanent evidence of authenticity for the non-sensitive collected readings. (3) Allow machine learning techniques and mathematical operations to be easily applied without exposing the secret information.

Another candidate technique to protect private information and seal transported data is steganography where a secret message is concealed within a larger transferred content (e.g. image or signal) in such a way that only the intended recipient can recover it [24]. However, simple steganography alone has two limitations. (i) It cannot ensure controlled access to the secret information because the hiding is performed in fixed positions (i.e. confidentiality issue). (ii) It cannot conceal large amounts of secret information (i.e. capacity issue). Although steganography has been widely studied and used in the multimedia domain [27], we demonstrated how it can be utilized to protect the privacy and authenticity in the context of streaming data [28], [29], [30]. However, due to the employed signal processing types (e.g. Walsh-Hadamard and wavelet), (1) the size of hidden information was very limited and (2) computational complexity was very high (e.g. \(O(n^2)\)) rendering them unsuitable in a limited resource environment.

A. Contribution

- We introduce a novel steganographic based privacy protection model surpasses existing models in terms of the appropriate balance between the volume of embedded secret data (i.e. up to 10 bits per coefficients), which was about 5-6 bits in our previous works [29], [30], and the resultant distortion (i.e. < 1%). This is due to the efficient utilization of DCT signal processing. This has been examined in details and showed in Section V.

  - We improve the mathematical computational complexity where we achieved a linear steganographic algorithm \(O(n)\) by employing a simple 1D DCT technique while improving the hiding security into two dimensional space. This has been mathematically investigated and presented in Section 5.

In the proposed model, the end-point IoT private information is randomly concealed inside the periodically collected normal streams and only authorized parties can recover this private data. This is achieved as follows. DCT is applied to the ordinary stream. The resultant coefficients are then reshaped to \(2D M \times N\) matrix employing an integrated random key (at the remote IoT side). Then, the key is applied to (1) only obfuscate the secret data (e.g. IDs, geometric location and location picture coupled with date and time) using a fast symmetric encryption, and (2) create an arbitrary sequence of coefficients which will be followed to conceal the private information. After the hiding process, an inverse DCT is employed to recompose the normal stream (i.e. stego readings) and transport them. Hence, only the parties who have the key (e.g. operation centers) can recover and decrypt the private data. The other benefit is that, the stego form of IoT stream can be utilized without removing the secret bits. Therefore, our algorithm will allow machine learning techniques and mathematical operations to be easily applied on stego streams without exposing the secret information.

II. RELATED WORK

Today, any proposed solution to the remotely collected IoT streams should carefully contemplate two main characteristics: security (i.e. solid end-to-end protection of the transmitted secret information and the authenticity of the transported streams) and efficiency (i.e. allowing mathematical operations to be directly applied without confidential information disclosure). However, these features are poorly balanced in most current solutions. Table I recaps most of the relevant work and classifies them into five categories based on the applied mechanisms: using simple, homomorphic cryptography, random perturbation and K-anonymity.

III. METHODOLOGY

A. The Discrete Cosine Transform

DCT is a widely-known transformation technique that can convert a stream into a set of frequency components called coefficients [32], [33]. This is important as it allows the resultant values to be categorized into an aware energy distribution where most of the important values can approximate the signal. The significant feature of this mechanism is that the actual signal can nearly be recomposed from only a few coefficients.

For a visual demonstration, Fig. 2 illustrates the impact of using DCT on a remotely collected stream. (a) The plot for >512 weather samples. (b) The resultant values after performing DCT, which obviously shows the distribution of the signal major energy (i.e. from 0 to <30), but others have lower importance. We accordingly wiped all coefficients between 30 and 512 to proof their impact on the recomposed stream. (c) The plot displays the recomposed original weather stream from only <30 coefficients. This obviously demonstrates the capacity and the flexibility that
TABLE I
RELATED MODELS SUMMARY.

| Protection mechanism              | Characteristics                                                                 | Notes                                                                 |
|-----------------------------------|---------------------------------------------------------------------------------|----------------------------------------------------------------------|
| Simple Cryptography [9], [10], [11], [12], [13], [14] | • Apply symmetric/asymmetric encryption at the remote side.  
• All data should be decrypted to perform mathematical operations.  
• All data have to be decrypted before usage. | • Weak Confidentiality.  
• Low Efficiency.  
• Keys’ management trouble. |
| Homomorphic Cryptography [15], [16], [17], [18] | • Apply homomorphic crypto at the remote side.  
• The obfuscated form of data can be utilized.  
• All data have to be decrypted before usage. | • Strong Confidentiality.  
• Not working with non-linear functions.  
• Not applicable in real applications.  
• Low Efficiency. |
| Random Perturbation [21], [22] | • Distribute noise along with the principal components.  
• Intermediate hops and Clouds can Not work accurately on the streams.  
• Legitimate recipient should take out the noise to fully understand. | • Not optimal with numeric and non-stationary streams [7].  
• No Confidentiality.  
• Weak Authenticity.  
• Medium Efficiency. |
| K- Anonymity [23], [25] | • Obfuscate the remote sender within a larger group.  
• Intermediate hops and clouds can not work accurately on the readings.  
• Focus on publishing an obfuscated-approximate data’s version for public usage. | • Has subtle privacy issues [31].  
• Weak Confidentiality.  
• Weak Authenticity.  
• Low Efficiency. |
| Steganography [28], [29], [30] | • Embed secret information inside IoT streams.  
• Intermediate hops and clouds can work accurately on the stego readings.  
• Using frequency domain for hiding. | • Low hiding capacity.  
• Non-linear computational complexity. |

DCT is selected for two main purposes. (1) Erasing or manipulating much of the resultant DCT coefficients will not impact the accuracy of the recomposed signal. (2) All resultant DCT’s coefficients are real numbers which allows us to directly manipulate and reconstruct, maintaining a minimum distortion, whereas the resultant values from other signal processing mechanisms (e.g. Fast Fourier and Chirp Z) contain an imaginary part that hardens the embedding process and maximizes the distortion. (3) Unlike other transformation techniques (Walsh-Hadamard and Wavelet), DCT is very flexible where it can be applied to any stream length.

Consequently, in this model, DCT is performed on various real-time IoT streams remotely collected from three different datasets - explained in Section [7] - which contains various readings such as chemical substances (e.g. ethanol), environment (e.g. temperature) and smart home activities (e.g. power consumption). The output is then reorganized to a 2D matrix. The most significant values will not be altered due to their significant representation to the original readings. In contrary, certain bits will be manipulated in the rest of DCT coefficients. However, to ensure the lowest noise to the original streams, many experiments have been done to choose a suitable steganography level (i.e. number of hidden bits in each coefficient) as presented in Fig 3. The experiments prove that, up to ≤10 (ten) bits can be arbitrarily concealed in the less significant coefficients without noticeable distortion effect.

B. Hiding

The private data will be concealed inside the resultant coefficients, after performing DCT to the collected streams. However, to ensure resilient security and to prohibit intruders from recovering this information, a security key is produced for every distributed IoT node and will be known only to the end receiver of the data. This key is used to enforce the following security layers.

1) Confidential Information Encryption: The key is used to obfuscate the private information (e.g. IDs) before the hiding process using symmetric cryptography (e.g. AES), which is secure and suitable for IoT’s abilities (See Fig 4). This is shown in Eq 5.

\[ \tilde{C} \equiv E(K, C) \] (3)
where $E$ is an AES algorithm, $K$ is the key, $C$ is the original private data and $\tilde{C}$ is the encrypted form.

2) Coefficients Scrambling: The key is employed to scatter and reorganize the resultant DCT coefficients from a vector to $2D M \times N$ matrix (See Fig 5).

Fig. 2. IoT readings: (a) Direct plot, (b) After applying DCT and (c) recomposed form after zeros more than 95% of DCT coefficients.

Fig. 3. Resultant distortion after concealing different number (i.e. 1 to 10) of bits in each DCT coefficient.

Fig. 4. An example of how the private information is obfuscated before hiding.

Fig. 5. Block diagram presents how the DCT coefficients are split, rescaled and converted into bits.
3) Random Hiding Order: The key is employed to create a random sequence of coefficients in a form of 2D matrix that will be used to conceal the private information. This is shown in Eq 4.

\[ \tilde{N} \times \tilde{M} \leftarrow f_x(K) \]  
(4)

where \( \tilde{N} \times \tilde{M} \) is the created 2D sequence of coefficients and \( f_x \) is the generation function.

For better understanding, Fig 5 shows a demonstration of using the key to produce an arbitrary hiding sequence. Step 1: the key is transformed into ASCII i.e., Default ASCII and an initial order is distributed i.e., Position Order. Step 2: the ASCII is then ordered in ascending manner i.e., Ascending Order. simultaneously, shuffle the Default Position to keep track of the original ASCII locations. Then, another sequence is assigned i.e., Ascending Position. Step 3: return the ASCII to its initial format by using the Default Position. A new unique sequence is obtained i.e., Descending Position \( \tilde{M} \). The reason of the 3 steps is to prevent two identical sequences from various keys. Step 4: by reversing the order, almost identical steps i.e., 1-3 are reiterated to generate \( \tilde{N} \). Finally, \( \tilde{M} \) and \( \tilde{N} \) are combined to compose the 2D matrix sequence. However, the key is much longer (e.g. \( \geq 128 \)) in the proposed model.

For better understanding, Fig 6 shows a demonstration of the key to produce an arbitrary hiding sequence. Step 1: the key is transformed into ASCII i.e., Default ASCII and an initial order is distributed i.e., Position Order. Step 2: the ASCII is then ordered in ascending manner i.e., Ascending Order. simultaneously, shuffle the Default Position to keep track of the original ASCII locations. Then, another sequence is assigned i.e., Ascending Position. Step 3: return the ASCII to its initial format by using the Default Position. A new unique sequence is obtained i.e., Descending Position \( \tilde{M} \). The reason of the 3 steps is to prevent two identical sequences from various keys. Step 4: by reversing the order, almost identical steps i.e., 1-3 are reiterated to generate \( \tilde{N} \). Finally, \( \tilde{M} \) and \( \tilde{N} \) are combined to compose the 2D matrix sequence. However, the key is much longer (e.g. \( \geq 128 \)) in the proposed model.

These three steps will guarantee that only an authorized receiver who has the security key can recover and decrypt the private information properly.

The detailed process of hiding is shown in Fig 4 5 and summarized in Fig 7. After applying DCT to the ordinary stream, the output is scattered and recomposed to \( M \times N \) 2D matrix. Then, the key is employed to obfuscate the private information. After that, the key is harnessed to create the random 2D sequence. The private bits will be then concealed corresponding to this order. The summary of all steps in this process is shown in section III-C.

C. Hiding Steps Summary

1) The private information is classified and obfuscated (i.e. using the key) \( \Rightarrow \) secret bits.

D. Inverse Discrete Cosine Re-Transform

The output of the embedding stage is named stego coefficients. The stego coefficients at this point is re-scattered to a vector, and the Inverse DCT applied to re-transform the collected streams to the initial time domain. The output of this process is Stego stream (i.e. comprises concealed private data) which is almost similar to the original stream. To make sure the selected coefficients are ready for steganography, they should be in an integer format and to avoid the issue of differentiating between negative and positive, all numbers should be positive. This may be done by adding a threshold \( \varphi \) and multiplied by \( \vartheta \) to maintain all their details (i.e. four decimal positions).

6) DCT coefficients are scattered \( \Rightarrow \) 2D \( M \times N \).
7) The hiding process is started.
8) After finishing, the resultant coefficients are rescaled by dividing all stego coefficients by \( \vartheta \) and subtracting the threshold \( \varphi \).
9) Re-combine coefficients and apply inverse DCT.
\[ x(n) = \sum_{n=1}^{N} w(k)g(k) \cos \left( \frac{\Pi(2n-1)(k-1)}{2N} \right) \] (5)

where \( k = 1, \ldots, N \) and,
\[ w(k) = \begin{cases} \frac{1}{\sqrt{N}} & \text{if } k = 1, \\ \frac{1}{\sqrt{2N}} & \text{if } 2 \leq k \leq N. \end{cases} \] (6)

### E. Private Information Recovery

To accurately extract and decrypt the private hidden bits, the security key has to be obtained. The process is nearly similar to the concealing steps, but the bits will be recovered rather than embedded. Fig. 8 demonstrates the recapped steps. First, DCT is applied to stego stream. The key is then employed to reorganize the DCT coefficients into a 2D form and create the selected coefficients’ sequence. Next, the secret bits’ recovery is started, corresponding to the produced order. Finally, the key will be used to decrypt the secret bits and verify the resultant information.

![Diagram of Private Information Recovery Process](image)

**Fig. 8.** The main steps to extract the sensitive information.

### IV. Evaluation

This section concentrates on the proposed model assessment from various angles such as the key robustness, hidden data security, the supreme size of private information that can be concealed and the distortion measurements.

#### A. Key Robustness

Both transmitted streams and the private key is required to be revealed in advance to recover the concealed secrets by legitimate parties. On the other hand, an anonymous intruder has to be aware of the existence of hidden message in addition to performing a brute force attack to break the model, which makes it extremely difficult.

However, the security key plays an important role in our model due to its usage to ensure various security layers (See Figs. 4, 5, and 6): (1) obfuscate the private information (2) reorganize DCT values into \(2D M \times N\) matrix, and (3) create a random coefficients’ sequence as \(2D \tilde{M} \times \tilde{N}\) matrix to conceal the bits. Therefore, the secrecy of this key is extremely important. The two involved parties should maintain this key very carefully. (a) At the first party (i.e. remote IoT), the key has to be integrated, and (b) the second party (e.g. operation centers) has to protect this key and employ it to recover and check the validity of the hidden private information whenever is required. Accordingly, Only stego streams are visible to other parties.

The key strength of our model can be quantified as the entropy bits’ number \(H\) (See Eq. 7) where \(2^H\) is the supreme possibilities that would need to be examined by anomalous intruders during a brute-force attack.

\[ H = \log_2 N^L \] (7)

Where \(L\) is the total symbols length and \(N\) is symbols’ probabilities. Table II presents a demonstration of different key lengths, key symbols sets and the total number of their possibilities.

**Table II**

| Key length | Symbol Set | Possibilities |
|------------|------------|---------------|
| 64         | US-ASCII   | 7.2e+134      |
| 128        | US-ASCII   | 5.2e+260      |
| 256        | US-ASCII   | ∞             |
| 64         | UTF-8      | 1.5e+154      |
| 128        | UTF-8      | ∞             |
| 256        | UTF-16     | ∞             |
| 128        | UTF-16     | ∞             |
| 256        | UTF-16     | ∞             |

### B. Unauthorized Retrieval

To protect the private embedded bits from brute-force recovery, the reorganized \(2D M \times N\) coefficients after DCT transformation of the collected streams have to be higher than arbitrary size (e.g. > Key volume) (See Eq 8).

\[ T_p = \sum_{i=r}^{C} C! \times N^L \] (8)

Where \(T_p\) is the combinations entropy, \(C\) and \(R\) are the reorganized \(2D\) coefficients and \(t\) is an offset which highlights the lowest entropy of each row selection. \(r\) refers to the highest entropy of the rows in \(R \times C\) matrix, and identically \(c\) refers to the maximum number of columns in that matrix.

For instance, assume collected streams of size 512 points, and reorganized to \(2D\) coefficients of \(32 \times 16\) after performing DCT. The chosen offset is \(16 \times 8\), the key charter set is UTF-8 and its volume is 128 (See Eq 9).

\[ T_p = \sum_{i=1}^{32} 32! \times \sum_{j=16}^{32} 32! \times 256^{128} \Rightarrow T_p = \infty \] (9)

Consequently, this confirms that recovering and decrypting the intended private data properly in a reasonable time is highly improbable.

#### C. Hidden Data Size

The maximum amount of hidden data in \(X\)-stream mainly depends on two values: (1) the stream’s size \(X\) (e.g. temperature) and (2) the hidden bits per coefficient.
However, if we use the streams directly even by hiding 1 bit per reading, the distortion will be high. One of the possible solutions is using signal processing to transform the readings from their time domain to frequency domain. Based on that, another dimension becomes very important to the hiding capacity which is the coefficients’ selection process. Therefore, this feature has been exploited in our model to exclude few important coefficients and hide more data in others to maximize the capacity with maintaining low distortion. In the proposed algorithm, the maximum number of bits that can be hidden in X transmitted stream with maintaining the lowest distortion impact is shown in Eq. 10

\[ b = \sum_{i=1}^{n} ((R \times C) - h) \times B \tag{10} \]

Where \( b \) is the highest entropy of hidden bits, \( n \) is the total streams samples, \( R \) and \( C \) are the rows and columns of the reorganized 2D coefficients after applying DCT transformation to the original values, \( h \) is the number of high sequence coefficients and \( B \) is the concealed bits in each coefficient.

For instance, suppose that DCT transformation is exercised to ordinary stream, and the size of the reorganized 2D matrix is 16 \( \times \) 512 (i.e. \( R \) and \( C \)). Also, suppose the high sequence coefficients is \( \leq 50 \) (i.e. the value of \( h \)) and about 9 bits (i.e. value of \( B \)) are concealed in each coefficient. Consequently, nearly 9159 bytes (9 KB) of private data can be concealed within these coefficients.

D. Stego Efficiency

To precisely evaluate our model’s impact on the collected streams, the margin between the ordinary and stego streams (i.e. resultant distortion) has been thoroughly monitored using percent of Percentage Residual difference (PRD). The PRD is a widely-used measurement that is known for its precision of detecting any recomposition error between the ordinary and the recomposed streams as defined in Eq. 11

\[ PRD = \sqrt{\frac{\sum_{n=1}^{N} (x(n) - \bar{x}(n))^2}{\sum_{n=1}^{N} (x^2(n))}} \times 100 \tag{11} \]

where \( x(n) \) and \( \bar{x}(n) \) are the ordinary and the recomposed streams, and \( N \) is the stream’s size.

The PRD measurement is also employed to accurately calculate the resultant distortion caused by the recovery process (i.e. between the ordinary and the extracted streams). All results are highlighted in Section V.

E. IoT Resource Constraints

Because of the IoT device limitations, the worst computational complexity (e.g. exponential) has been avoided during the developing of the algorithm’s functionalities. Therefore, the worst-case complexity has been examined in two ways. (1) As shown in Table III big \( O \) notations have been used. The majority of the functions are designed as linear tasks. It should be noted that Scattering and Sequence generation has been improved from quadratic to linear due to the utilization of radix sorting. From that, our algorithm is fully compatible with the new wireless network standards called IEEE 802.15.4/ZigBee [36]. IEEE 802.15.4/ZigBee standards are already running algorithms with the computational complexity of logarithmic \( O(n \log n) \) and quadratic \( O(n^2) \) [37], [38]. (2) All streams in the repositories have been used and the execution time proved to be very low - < 0.025 seconds - as presented in Fig 9.

The main tasks of the concealing model (See Table III) that has to be executed by the remote IoTs are DCT and its inverse, random sequence formulation, private information scattering and embedding. Firstly, let’s suppose \( f(n) \) is \( O(g(n)) \) if \( f \) develops at farthest as \( g \). Consequently, \( f(n) = O(g(n)) \) only if there occurs \( c, n_0 \in \mathbb{R}^+ \) such that for all \( n \geq n_0, f(n) \leq c.g(n) \). From that, for each 1D vector of a stream of length \( n \) (i.e. 500 to 2048 in our experiments), the extreme complexity will be as follows. (i) \( O(n) \) for the time and space needed for DCT and its inverse [32]. (ii) \( O(nk) \) for creating random sequences using a constant key size \( k \in \mathbb{Z} \) after its enhancement to the linear problem. The space needed is the summation of \( n \) and \( k \). (iii) The extreme required complexity for scattering the private information of length \( m \) where at the lowest \( < n/2 \) is \( O(m) \). (iv) \( O(nb) \) for concealing \( b \in \mathbb{Z} \) (i.e. 1 to 10) bits in each coefficient of maximum length \( n \), but the needed space is the accumulation of both \( n \) and \( m \).

It is obvious from the table that there is stability in the complexity in all three cases. This is due to the careful usage of the DCT in its simplistic form (i.e. 1D) and improving it by linear mathematical operations to achieve the required level of protection.

### TABLE III

| Algorithm Functionalities | Computational Complexity |
|---------------------------|--------------------------|
| **Complexity** | **Time** | **Space** |
| Best | Average | Worst | Best | Average | Worst |
| DCT/Inverse | \( O(n) \) | \( O(n) \) | \( O(n) \) | \( O(n) \) | \( O(n) \) | \( O(n) \) |
| Random Order | \( O(nk) \) | \( O(nk) \) | \( O(nk) \) | \( O(n + k) \) | \( O(n + k) \) | \( O(n + k) \) |
| Scramble Sensitive | \( O(m) \) | \( O(m) \) | \( O(m) \) | \( O(m) \) | \( O(m) \) | \( O(m) \) |
| Embedding | \( O(nb) \) | \( O(nb) \) | \( O(nb) \) | \( O(n + m) \) | \( O(n + m) \) | \( O(n + m) \) |

V. EXPERIMENTS AND RESULTS

A. Datasets

To test the effectiveness of our model with different types of non-stationary streams data, three datasets have been examined. (1) Chemical dataset gathered and distributed by the University of California, Irvine Research Group [39]. It contains extensive periodical readings over three years for six different volatile organic compounds: ethanol, ethylene, ammonia, acetaldehyde, acetone and toluene. (2) Environment dataset collected and published by Intel Berkeley Research Lab [40]. It offers detailed continues readings (i.e. every 31 seconds) over three months for four environmental characteristics: humidity, temperature, voltage and light. (3) Smart Homes dataset collected and published as a part
of "Project Smart*" by Laboratory for Advanced System Software [41], [42]. It contains comprehensive periodical readings over three months (every minute) for different homes. The types of streams are power consumption, heat-index, inside/outside weather, inside/outside moisture and wind-cold. It also offers the utility consumption (electricity) from nearly 400 anonymous houses every minute for \((24 \times 30 \times 3)\) hours.

**B. Experiments**

In this paper, all the above types of streams were used to thoroughly prove the feasibility of implementing the proposed algorithm on various collected streams. For all, experiments were done to conceal and recover the private data based on our algorithm steps presented in Sections III-B and III-E. The secret bits was a set of values that have to be private such as location ID, geometric location, location picture, date and time which all transformed into bits to be concealed inside the transmitted streams.

Our tests can be distributed into the following. (1) Hiding, which is done by remote IoT sensors to hide the remote locations’ private data in their collected streams as presented in Section III-B. (2) Private information recovery that is at the receiver’s end as described in III-E. Consequently, if the transmitted stego streams that contain the hidden private bits are sniffed or brutally altered by unauthorized parties, (1) it will not disclose any private information and (2) it can be easily examined and verified.

To obtain neutral and unbiased results, detailed experiments were performed with ranges of key sizes in addition to various collected streams having lengths (e.g. 512-to-4096). To highlight the extreme distortion impact, all detailed low sequence DCT values (i.e. around 95% of the total coefficients) have been employed. For brevity, only a few examples of our results are presented, (1) Fig. 10 shows an instance using the chemical dataset of a plot of 6 ordinary streams used to conceal private data, the stego and the extracted forms. (2) Fig. 11 shows an example using environment dataset of another plot of 4 ordinary streams, and the stego form before and after the extraction process. (3) Fig. 12 presents another example using smart homes dataset of a plot of 7 ordinary streams in addition to their stego and extracted forms. (4) Tables IV, V and VI show the PRD measurements from all aforementioned datasets’ streams between the actual and stego forms in addition to actual and the recovered forms.

**C. Discussion**

Despite the various sample lengths of the streams and various values’ ranges, all PRDs are < 1%. This proves that the influence will only be to the less significant decimal digits (i.e. third or fourth) that typically are ignored. This guarantees that our technique will have stable and little distortion impact on the actually transmitted streams. On the contrary, it offers a promising solution with a paradigm shift for protecting the privacy of the transmitted private information as well as the originality of the periodically collected streams. The merits of this solution are as previously stated. (1) There are robust end-to-end privacy protection and authenticity where the hidden secured information can only be recovered and verified by legitimate recipients (e.g. operation centers), whereas others can only see the stego form which is almost similar to the original streams. (2) There is no increase in the actually transmitted streams. (3) There is no change to the original stream’s form which helps the legitimate receivers to directly exploit operational administration such as cloud providers’ services without disclosing private information. In other words, all mathematical operations can be directly applied to the transmitted stego form of streams even at intermediate hopes and cloud while maintaining the privacy and authenticity.

**D. Comparison with Existing Models**

The comparison focuses on two folds. Firstly, the superiority of this model over our previous steganographic-based
techniques in the context of IoT streams [28], [29], [30] which has been summarized in Table VII. Secondly, there are recent works proposed by Vongurai and Phimoltares [43], Biswas et. al. [44], and Bhaskar et. al. [45] that have similar signal processing (i.e. DCT) with a different context (i.e. multimedia domain). Therefore, our work is compared with these three recent techniques where (1) in [43], the authors used DCT decomposition to conceal a secret message inside transmitted JPEG image; (2) the authors in [44] utilized DCT to hide a secret data inside a colored image using a predefined password; (3) the authors in [45] applied DCT to hide a secret content inside transmitted MPEG-4 videos.

The proposed technique has the following improvements.

1) After experimenting with the same number of the transmitted collected streams, it is clear from Fig. 14 that the capacity of the hidden secret information is much higher in our algorithm than in models [43], [44], [45] where up to 10 bits can be concealed in each DCT value because of exploiting the least significant DCT coefficients, whereas just 1 to 2 bits can be concealed in their algorithms.

2) From Fig. 13 it should be noticed that our algorithm has less resultant distortion than other algorithms.
because it has been designed specifically to be aware of the sensitivity of the important features of the numeric data, whereas other algorithms designed to widen content (e.g. images and videos).

3) Most significantly, our model is strongly secure compared to the models in [43], [44], [45] due to their static and immediate secret bits distribution in the absence of a strong key or using just a simple password, but in our model various security layers are implemented which are scattering the resultant DCT values, obfuscating the private bits and producing a random sequence derived from the key to dynamically distribute the bits among arbitrary coefficients.

VI. CONCLUSION

In this work, a new secure steganographic technique has been introduced to protect privately transmitted information with streams by distributing them randomly employing a secret key. This will provide (1) robust end-to-end privacy protection for sensitive information, and (2) strong proof of originality for the normal streams. To ensure the highest hiding capacity, DCT is applied to compose the readings into a group of coefficients. To guarantee minimum distortion, only the least significant values are used. To strengthen the security, a key is used to (1) only obfuscate the private information, (2) reorganize the coefficients into a $2D M \times N$, and (3) create a random order

**TABLE IV**

| Segment No | PRD % Stego | PRD % Recovered | PRD % Stego | PRD % Recovered |
|------------|-------------|----------------|-------------|----------------|
| 1          | 0.1989      | 0.2437         | 0.1887      | 0.2284         |
| 2          | 0.3068      | 0.3611         | 0.6665      | 0.7834         |
| 3          | 0.0529      | 0.0668         | 0.3137      | 0.4126         |
| 4          | 0.0399      | 0.0747         | 0.2304      | 0.2858         |
| 5          | 0.0301      | 0.0377         | 0.1206      | 0.1498         |
| 6          | 0.0648      | 0.0485         | 0.4974      | 0.5928         |
| 7          | 0.0432      | 0.0831         | 0.1839      | 0.2139         |
| 8          | 0.0937      | 0.1157         | 0.1042      | 0.1266         |
| 9          | 0.3214      | 0.3797         | 0.6452      | 0.8083         |
| 10         | 0.1954      | 0.2220         | 0.2375      | 0.2842         |
| 11         | 0.1887      | 0.2284         | 0.2376      | 0.2789         |
| 12         | 0.5813      | 0.6949         | 0.9745      | 0.2384         |
| 13         | 0.5643      | 0.4494         | 0.3666      | 0.4524         |
| 14         | 0.2465      | 0.5152         | 0.4162      | 0.4973         |
| 15         | 0.3676      | 0.6361         | 0.6326      | 0.7817         |
| 16         | 0.1453      | 0.1797         | 0.1804      | 0.2268         |

**TABLE V**

| Segment No | PRD % Stego | PRD % Recovered | PRD % Stego | PRD % Recovered |
|------------|-------------|----------------|-------------|----------------|
| 1          | 0.0708      | 0.1033         | 0.3492      | 0.3514         |
| 2          | 0.0723      | 0.1030         | 0.0538      | 0.0674         |
| 3          | 0.0717      | 0.0914         | 0.0914      | 0.0850         |
| 4          | 0.0707      | 0.0906         | 0.0724      | 0.0889         |
| 5          | 0.0779      | 0.1081         | 0.2582      | 0.2255         |
| 6          | 0.0787      | 0.1086         | 0.0549      | 0.0662         |
| 7          | 0.0700      | 0.0964         | 0.1544      | 0.1572         |
| 8          | 0.0686      | 0.0965         | 0.0573      | 0.0654         |

**TABLE VI**

| Temperature | PRD % Stego | PRD % Recovered | PRD % Stego | PRD % Recovered |
|-------------|-------------|----------------|-------------|----------------|
| 9           | 0.0220      | 0.0253         | 0.0360      | 0.0611         |
| 10          | 0.0606      | 0.0750         | 0.6076      | 0.4837         |
| 11          | 0.0334      | 0.0376         | 0.7041      | 0.4613         |
| 12          | 0.4276      | 0.4276         | 0.7204      | 0.4886         |
| 13          | 0.0138      | 0.0170         | 0.8362      | 0.9902         |
| 14          | 0.0521      | 0.0645         | 0.3728      | 0.5115         |
| 15          | 0.0551      | 0.0663         | 0.7130      | 0.4661         |
| 16          | 0.0182      | 0.0218         | 0.7053      | 0.4382         |
TABLE VI
PRD RESULTS FOR SMART PROJECT DATA SET READINGS

| Power            | Heat-Index |
|------------------|------------|
| Segment No       | PRD % Stego | PRD % Recovered | PRD % Stego | PRD % Recovered |
| 1                | 0.1019     | 0.1019          | 0.0346     | 0.0411          |
| 2                | 0.0076     | 0.0091          | 0.0334     | 0.0409          |
| 3                | 0.0077     | 0.0094          | 0.0337     | 0.0399          |
| 4                | 0.0132     | 0.0155          | 0.0311     | 0.0391          |
| 5                | 0.0131     | 0.0158          | 0.0306     | 0.0390          |
| 6                | 0.1113     | 0.1173          | 0.0321     | 0.0388          |
| 7                | 0.1148     | 0.1148          | 0.0317     | 0.0416          |
| 8                | 0.0901     | 0.0901          | 0.0324     | 0.0377          |

TABLE VII
COMPARISON OF IOT STREAMS STEGO-BASED SOLUTIONS AND OUR APPROACH

| Feature                  | MD [39] | MD [40] | MD [41] | Our Algorithm |
|--------------------------|---------|---------|---------|---------------|
| Signal processing        | Walsh-Hadamard | Wavelet | DCT     |               |
| Complexity               | O(\(n \log n\)) | O(\(n^2\)) | O(\(n\)) |               |
| Hiding per/coefficient   | 6       | 6       | 10      |               |

Fig. 13. Resultant distortion after applying our algorithm and the algorithms in [43], [44], [45] on the same amount of numerical data. (a) PRDs between the original and stego form, (b) PRDs between the original and the extracted form.

Fig. 14. Comparison for the maximum amount of secret data that can be hidden between our algorithm and the algorithms in [43], [44], [45].

resultant distortion has been carefully measured in all stages - the original, the stego, and the extracted forms - using a well-known measurement called PRD. After thorough experimentation on three different types of streams (i.e. chemical, environment and smart homes) it has been proven that our model has little impact on the actual readings (< 1%). Also, computational complexity has been proven to be much lighter \(O(n)\) compared to existing work.

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