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# 基于 LSTM 的激光混沌同步通信

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**摘 要:**针对激光混沌保密通信系统中混沌信号接收双方硬件参数难以完全匹配的问题,用长短期记忆神经网络对发射端产生的大量混沌加密信号和部分载波信号进行充分训练,最终得到一个与发射端激光器系统高度相似的神经网络模型,并用此非线性模型代替接收端进行解密,实现了 2 Gbit/s 的混沌同步通信。该方法明显降低了混沌同步的复杂性。探讨了不同节点数量、耦合系数以及信噪比对于同步通信的影响,结果表明同步系数可以高达 0.999 966,均方根误差达到  $10^{-3}$  量级,误码率低至  $10^{-10}$  量级。最后通过图像传输系统验证了方案的可行性。

**关键词:**激光通信;混沌同步;长短期记忆神经网络;光反馈;光电反馈;混沌预测

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## 0 引言

混沌自 1990 年被首次提出以来,由于其类随机性、速率高、鲁棒性强等优点,在光通信物理层加密方面得到广泛研究<sup>[1-4]</sup>。但是在传统的混沌同步光通信系统中,需要使发射端与接收端激光器器件参数高度匹配,现实中很难达到这种理想情况,因此传统混沌光通信面临着硬件系统复杂和同步系数低等问题<sup>[5-7]</sup>。

深度学习技术具有强大的非线性均衡能力<sup>[8]</sup>,在处理非线性模型方面具有巨大优势,近年来被广泛应用于监测、分类、预测等领域<sup>[9-11]</sup>。很多学者也将其应用于光通信研究中<sup>[12-20]</sup>,针对传统混沌光通信系统,用神经网络强大的非线性拟合能力来代替接收端,实现高质量混沌通信。2019 年,KE Junxiang 等提出利用全连接神经网络预测混沌载波的方案,实现了 32 Gbit/s 信号的混沌同步通信<sup>[21]</sup>。2022 年,刘家跃等利用储备池神经网络代替混沌光通信接收端,实现了较高质量的混沌同步通信<sup>[22]</sup>。上述研究相较于传统光通信系统,均极大降低了混沌同步复杂度并简化了通信系统整体结构,然而在神经网络结构方面,两者选择了多隐藏层或者多节点的结构,因此会在一定程度上增大时间损耗和计算成本,同时还存在着梯度爆炸的可能性。

长短期记忆(Long Short-Term Memory, LSTM)神经网络作为一种有记忆性的预测型算法,具有学习长期依赖关系的能力,以及解决梯度爆炸问题与强鲁棒性的优势,被广泛应用于性能监测和时间序列预测等<sup>[23-27]</sup>。2019 年,MUZAFFAR 等利用 LSTM 网络对电负荷进行预测,在短期和长期预测方面都取得了较好的效果,表明 LSTM 神经网络作为一种特殊类型的循环神经网络,其长期和短期学习能力适合于时间序列的建模和预测的应用<sup>[23]</sup>。2020 年,SANGIORGIO 等在四个标准混沌动力学系统中对 LSTM 神经网络多步预测性能进行了分析,结果表明 LSTM 表现出良好预测性能的同时具备优化梯度和强鲁棒性的优势<sup>[24]</sup>。2021 年,YE Huangbin 等利用低带宽相干接收机获取时域样本,并用 LSTM 神经网络作为分类器成功实现光学信噪比(Signal Noise Ratio, SNR)监测,同时系统具有较高的分类精度和鲁棒性,计算复杂度较低<sup>[25]</sup>。2021 年,GAO Xiaojing 等利用 LSTM 神经网络进行光学混沌系统的无模型时滞特征提取,减少数据量的同时提高了识别效率<sup>[26]</sup>。

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本文在讨论光反馈和光电反馈产生混沌信号的基础上,提出基于LSTM神经网络的混沌同步保密通信系统模型,同时利用交叉预测算法有力提高混沌同步质量<sup>[28]</sup>,以达到良好的混沌同步通信效果。

## 1 LSTM混沌同步原理与方法

LSTM神经网络的混沌通信系统结构如图1所示。激光混沌系统产生随机混沌载波信号 $c(t)$ ,信息系统产生信息信号 $M(t)$ (该 $M(t)$ 包含原始有用信息和随机噪声信号),两者经由一定的混合比耦合形成加密信号 $u(t)$ ,随后加密信号作为神经网络的输入。在线下训练阶段,进一步利用交叉预测算法对网络模型进行优化,基于无限可观测的已知输入变量和有限可观测的已知输出变量来构建非线性网络,使LSTM网络可以根据输入变量自动推断出不可观测阶段的目标输出变量。加密信号 $u(t)$ 和混沌载波信号 $c(t)$ 分别作为神经网络的输入变量和目标输出变量,神经网络的每次迭代都会对其网络节点状态进行更新,直至达到理想的损失值为止,训练效果越好,神经网络对于接收端拟合度越高,预测得到的混沌载波与目标载波之间精度越高。此时标志着该训练结束的神经网络能够较好地替代混沌光通信接收端。在测试阶段,神经网络节点状态已经确定,接收到输入变量 $u(t)$ 后,系统会自动映射输出预测载波信号 $c'(t)$ ,随后由加密信号 $u(t)$ 减去预测载波信号 $c'(t)$ 即可解密得到信息信号 $M'(t)$ 。

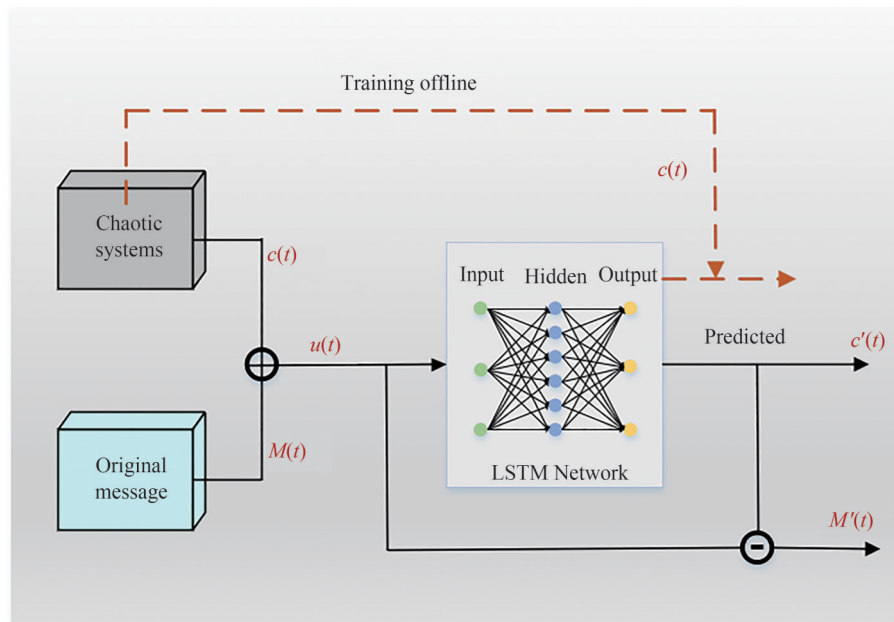


图1 LSTM通信系统原理

Fig.1 The principle of LSTM communication system

## 2 实验设计与仿真分析

### 2.1 光反馈混沌同步通信

设计的基于LSTM的光反馈混沌同步通信系统如图2所示<sup>[5,22]</sup>。波长为1550 nm的半导体激光器(Laser Diode, LD)LD1输出连续光,经过外部的反射镜反馈回激光器并对其进行扰动,随后输出的光经过光纤隔离器(Optical Isolator, ISO)和可变光衰减器(Variable Optical Attenuator, VOA)VOA1后,由一个50:50的光耦合器(Optical Coupler, OC)OC2分为两束,一束被光电探测器(Photodetector, PD)PD1接收,该束光信号用于神经网络输出端线下训练数据。另一束与信息光 $m(t)$ 通过光纤耦合器OC1进行混合形成原始加密信号 $c(t)+m(t)$ 。该信息光由非归零码(Not Return to Zero, NRZ)信号驱动的马赫增德尔调制器(Mach-Zehnder Modulator, MZM)调制波长为1550 nm的半导体激光器LD2产生,随机NRZ信号由任意波形发生器(Arbitrary Waveform Generator, AWG)产生,混沌信号和信息信号的混合比由光衰减器VOA1和VOA2控制。原始加密信号在信道传输过程中受到噪声 $n(t)$ 影响,最终形成加密信号 $u(t)$ ,此时加密信号包

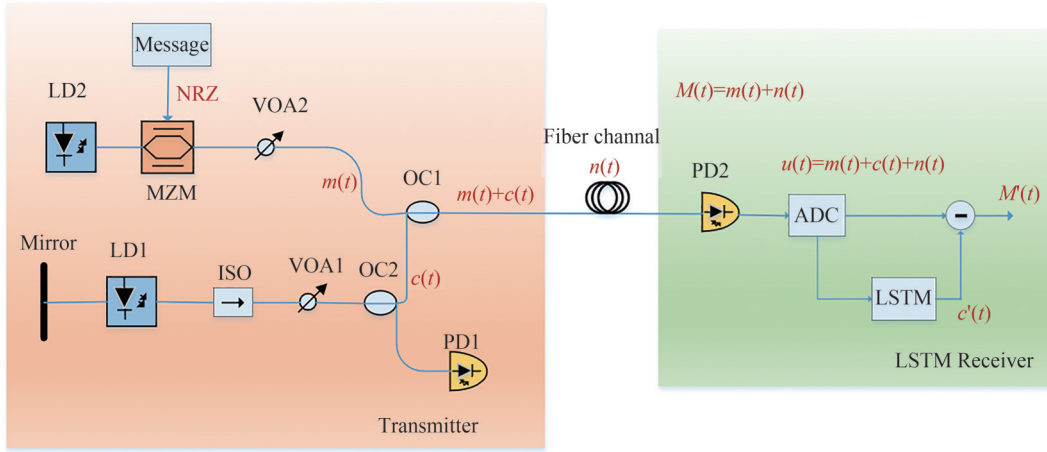


图2 基于LSTM的光反馈通信系统

Fig.2 The schematic of optical feedback communication system based on LSTM

括噪声  $n(t)$ 。在接收端光电二极管 PD2 接收到加密信号为  $u(t)=c(t)+m(t)+n(t)$  并将其转化为电信号后,模数转换器 (Analog to Digital Converter, ADC) 将模拟信号转换为数字信号,一路经过提前训练好的 LSTM 神经网络生成与发送端高度拟合的混沌载波,随后利用接收到的加密信息减去同步后的混沌载波,即可解密出有用信息。本文仅讨论近距离光纤通信,所以忽略了信道损伤对系统造成的影响。对于长距离光纤通信,需要对色散等光纤损伤进行补偿。

发射端系统动力学可由 Lang-Kobayashi 方程建模为<sup>[5,22]</sup>

$$\frac{dE}{dt} = \frac{1}{2} (1 + i\alpha)G(N, |E|^2)E + k_f E(t - \tau_f) e^{-i\omega\tau_f} \quad (1)$$

$$\frac{dN}{dt} = \frac{I}{e} - \gamma_e N - [G(N, |E|^2 + \gamma_p)] |E|^2 \quad (2)$$

$$G(N, |E|^2) = \frac{g(N - N_0)}{1 + s|E|^2} - \gamma_p \quad (3)$$

式中,  $E$  为激光器腔内复电场强度;  $t$  为时间;  $\alpha$  为线宽增益因子;  $N$  为激光器腔内载流子密度;  $k_f$  为反馈强度;  $\tau_f$  为反馈时延;  $\omega$  为激光器角频率;  $I$  为激光阈值电流;  $e$  为每电子电荷;  $\gamma_e$  为载流子衰减速率;  $g$  为微分增益系数;  $N_0$  为透明载流子数;  $s$  为饱和系数;  $\gamma_p$  为光子衰减速率;  $G$  为增益函数。

系统动力学方程利用 Matlab 中四阶 Runge-Kutta 法进行求解,结合文献[5]设置参数如表 1。

表 1 仿真参数

Table 1 Parameters values in simulation

Symbol	Description	Value
$\alpha$	Line width enhance factor	3
$k_f$	Feedback intensity of SL	$30 \text{ ns}^{-1}$
$\tau_f$	Feedback delay of SL	1.2 ns
$\gamma_e$	Carrier decay rate	0.65 ns
$I$	Bias current	38.06 mA
$\gamma_p$	Photon decay rate	$496 \text{ ns}^{-1}$
$g$	Differential gain	$1.2 \times 10^{-5} \text{ ns}^{-1}$
$N_0$	Transparent carrier number	$1.25 \times 10^8$
$s$	Saturation coefficient	$5 \times 10^{-7}$

对于发送端,光反馈半导体激光器系统产生的混沌信号作为混沌载波序列,采用 SNR 为 30 dB 的二进制非归零信号作为有噪信息,两者通过一定比例  $A$  混合作为混沌加密信号,混合比  $A$  表示为有噪信息与混

沌载波序列的峰峰值之比,即

$$A = \frac{M_{pp}}{C_{pp}} \quad (4)$$

式中,  $M_{pp}$  表示有噪信息的峰峰值,  $C_{pp}$  表示混沌载波序列的峰峰值。为了确保系统安全性,同时获得较好的加密效果,将混合比  $A$  设置为 0.08 进行混沌同步通信研究。

为了衡量神经网络系统的预测效果,通过式(5)来计算均方根误差(Root Mean Square Error, RMSE)。

$$\text{RMSE} = \sqrt{\frac{1}{N_u} \sum_{i=1}^{N_u} (Y_i - X_i)^2} \quad (5)$$

式中,  $N_u$  为测试集取样点数,  $Y_i$  为神经网络的预测输出值,  $X_i$  为对应的真实目标值。

为了检验系统混沌同步质量,引入相关系数  $C$ , 定义为

$$C = \frac{\langle (x[n] - \langle x[n] \rangle)(y[n] - \langle y[n] \rangle) \rangle}{\sqrt{\langle [x[n] - \langle x[n] \rangle]^2 \rangle \langle [y[n] - \langle y[n] \rangle]^2 \rangle}} \quad (6)$$

式中,  $x[n]$  为目标混沌载波序列,  $y[n]$  为预测混沌载波序列,  $\langle \dots \rangle$  表示平均值。相关系数越大,表明发射端与接收端混沌序列同步程度越高,越有利于精确解密。

将 20 000 个数据集的前 80% 数据划分为训练集,后 20% 分为测试集,光反馈系统中发射端混沌载波序列、原始信息 NRZ 信号、叠加 30 dB 噪声的有噪信息以及加密信息波形如图 3 所示。观察混沌序列与加密信息可知,两者幅值差距极小以至难以区别,说明混合比为 0.08 的信息有效耦合到了混沌序列中。

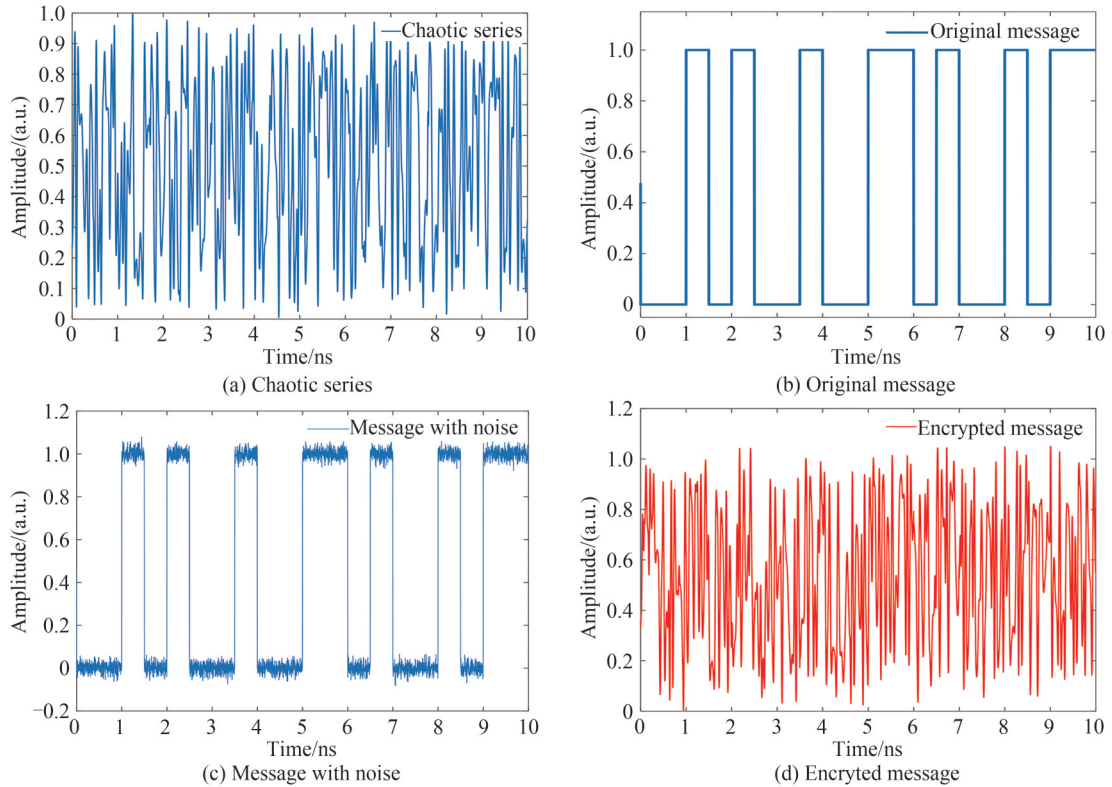


图3 光反馈系统中发射端信息序列

Fig.3 The message series of transmitter in optical feedback system

神经网络结构包含 200 个 LSTM 节点、一个丢弃率为 0.5 的舍弃层,以及一个全连接层,其中使用到的训练优化器为 adam。通过调节网络的训练参数达到理想仿真结果,在光反馈系统中训练过程的损失函数随迭代周期的变化趋势如图 4 所示,可知训练后期均方根误差(Root Mean Square Error, RMSE)和损失函数 Loss 均变得平稳且趋近于零值。系统最终实现耦合系数为 0.08,信噪比为 30 dB,传输速率为 2 Gbit/s 的加



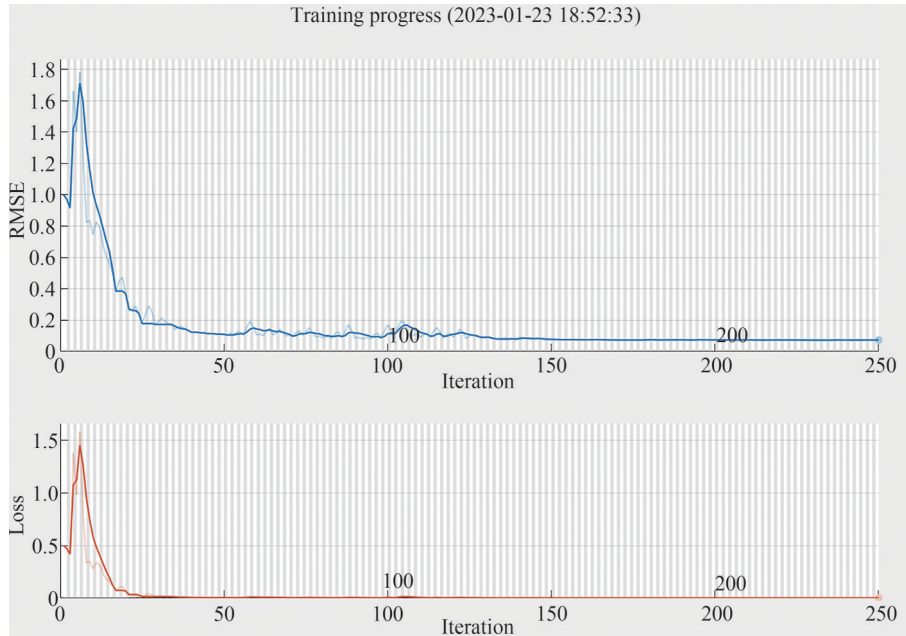


图4 光反馈系统中训练过程的损失函数随迭代周期的变化趋势

Fig.4 The variation trend of loss function with iteration period during the training progress in optical feedback system

密信号的混沌同步通信。经过LSTM神经网络对激光混沌系统进行建模训练后,接收端混沌同步以及解密如图5所示。图5(a)中横纵坐标分别为真实的目标混沌序列和LSTM预测的混沌序列,两者高度相似,大部分都拟合在 $y=x$ 直线上,经计算预测 $RMSE = 8.866 \times 10^{-3}$ ,系统同步系数高达0.9997,说明系统预测效果较好且具有高质量的混沌同步性。

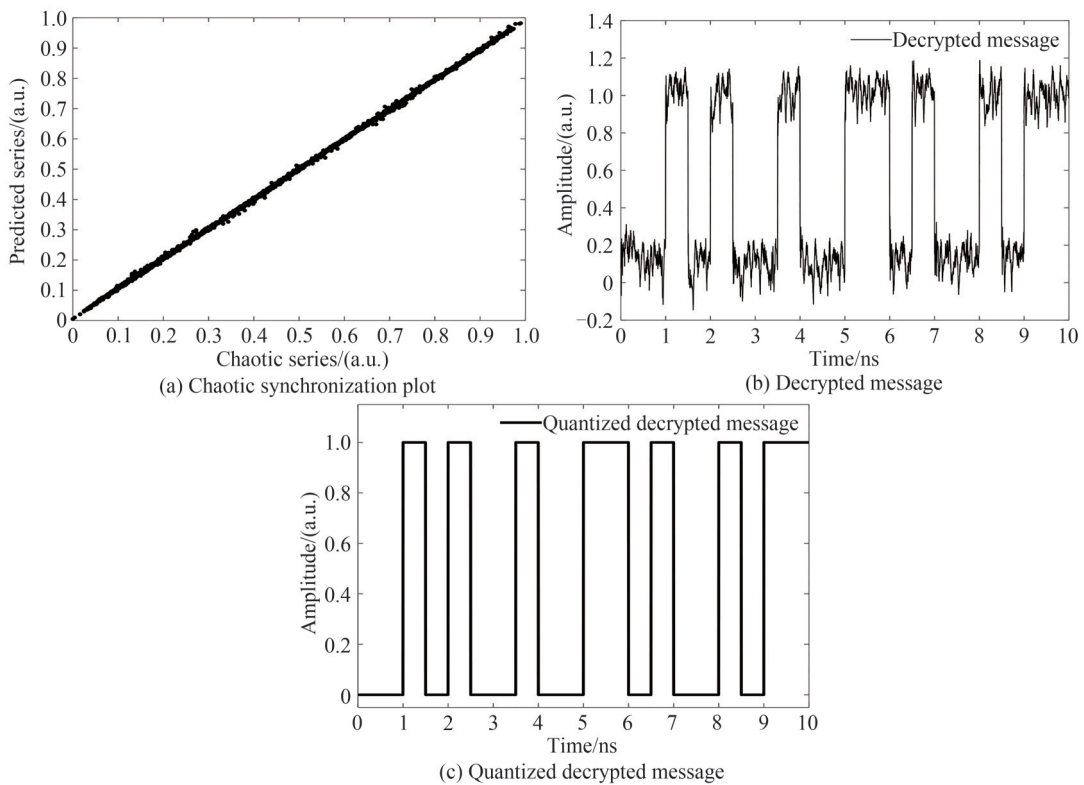


图5 光反馈系统中接收端解密信息

Fig.5 The decrypted message of receiver in optical feedback system

由接收端获取的加密信息直接减去经神经网络预测的混沌载波解调出的有噪信息如图5(b)所示,信号分布在1和0附近,此时解密信息中包含着轻微噪声,利用Q因子计算误码率(Bit Error Rate, BER)为 $1.16 \times 10^{-10}$ ,可见BER远低于硬判决前向纠错阈值标准(Hard Decision threshold of Forward Error Correlation standard, HDFEC)值 $3.8 \times 10^{-3}$ ,说明系统具备高质量的混沌同步通信能力<sup>[22,29]</sup>。经过量化解调后的信息如图5(c)所示,其与原始信息图3(b)几乎相同,系统通信质量较高。

## 2.2 光电反馈混沌同步通信

为了验证LSTM神经网络的通用性,研究光电反馈混沌同步通信系统,基于LSTM的光电反馈通信系统如图6所示<sup>[21,26]</sup>。

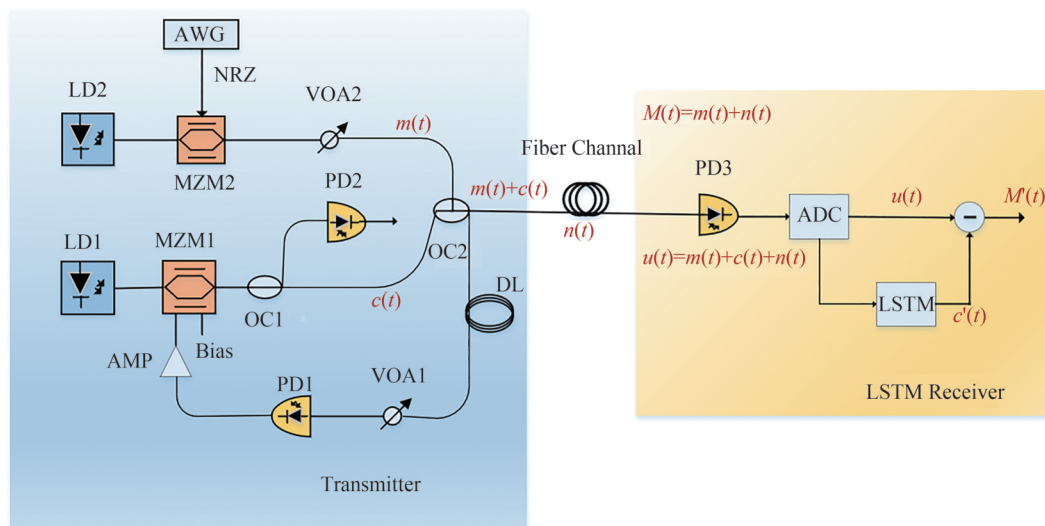


图6 基于LSTM的光电反馈通信系统

Fig.6 The schematic of photoelectric feedback communication system based on LSTM

由半导体激光器LD1产生的连续光被具有强烈非线性的MZM1调制,调制器的输出光经过光电耦合器OC1分为两部分,一部分载波信号由光电二极管PD2接收,用于线下神经网络训练;另一部分通过光耦合器OC2与原始有用信息混合形成新的无噪加密信号,其中有用信息由半导体激光器LD2和MZM2调制而成,该加密信号的混合比可由可变光衰减器VOA1和VOA2调节。随后经OC2耦合而成的无噪加密信号一部分用于安全传输,另一部分用于反馈回路产生混沌。在光纤传输信道中受到噪声 $n(t)$ 干扰,形成有噪加密信号。光电探测器PD3在接收端接收有噪加密信号后,将光信号转化为电信号,随后经过模数转换器(Analog Digital Converter, ADC)将模拟信号转换为数字信号,经过提前训练好的LSTM神经网络实现混沌同步,产生与发送端高度拟合的混沌载波,随后利用接收到的有噪加密信息减去同步后的混沌载波,即可解密出有用信息。

该光电反馈混沌系统动力学方程为<sup>[18,26]</sup>

$$x(t) + \gamma \frac{dx(t)}{dt} + \frac{1}{\theta} \int x(s) ds = \beta \cos^2[x(t - T_0) + \Phi_0] \quad (7)$$

式中, $\gamma$ 和 $\theta$ 为系统特征响应时间, $\beta$ 为环路反馈增益, $T_0$ 为延迟时间, $\Phi_0$ 为调制器直流偏置。在仿真实验中, $\gamma = 5.3$  ps, $\theta = 5.3$  us, $T_0 = 30$  ns, $\Phi_0 = 0$ 。动力学方程通过Matlab中四阶Runge-Kutta法进行求解。

光电反馈系统中仍将20 000个数据集的前80%数据划分为训练集,后20%分为测试集,发射端混沌载波序列、原始信息NRZ信号、叠加30 dB噪声的有噪信息以及加密信息波形如图7所示。观察混沌序列与加密信息可知,两者差别很小,说明混合比为0.08的信息有效隐藏到了混沌序列中。

通过调节网络的训练参数达到理想仿真结果,光电反馈系统中训练过程的损失函数随迭代周期变化趋势如图8所示,可知训练后期RMSE和Loss均变得平稳且趋近于零值。

经过LSTM神经网络对激光混沌系统进行建模训练后,接收端混沌同步以及解密如图9所示。在

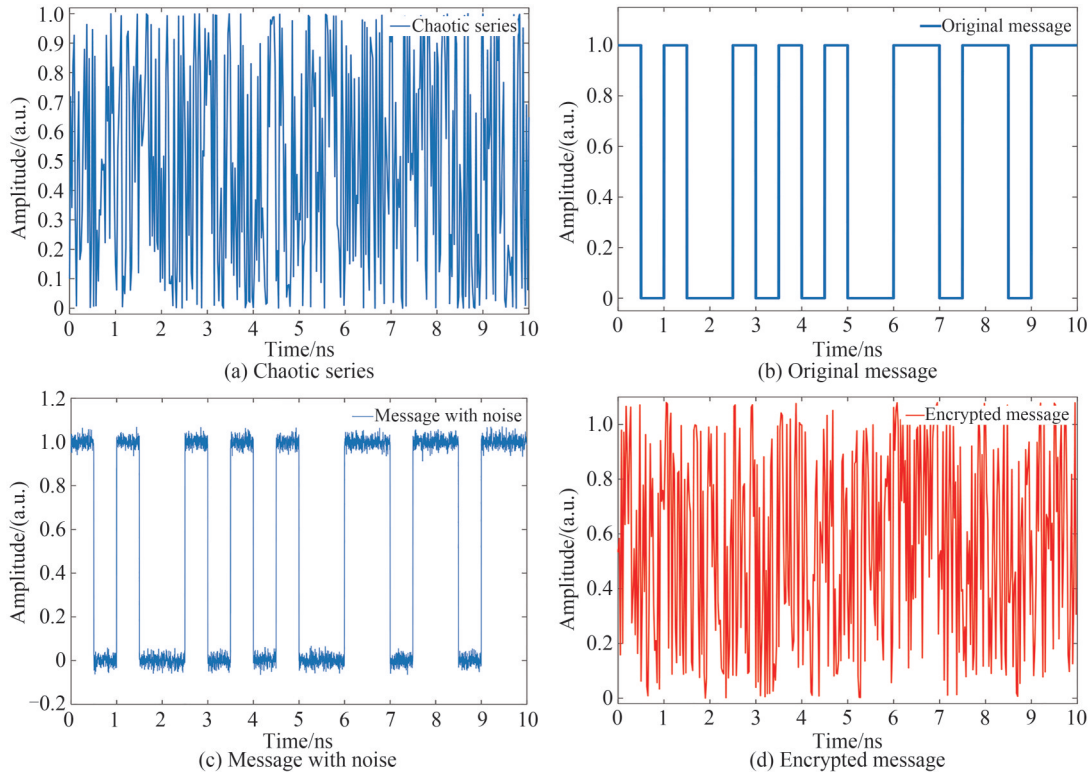


图7 光电反馈系统中发射端信息序列

Fig.7 The message series of transmitter in photoelectric feedback system

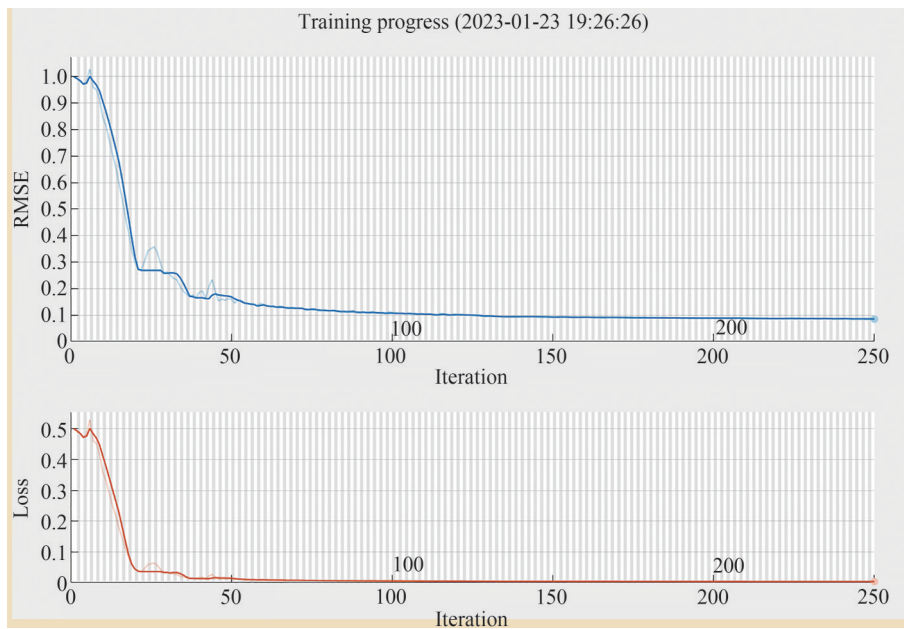


图8 光电反馈系统中训练过程损失函数随迭代周期的变化趋势

Fig.8 The variation trend of loss function with iteration period during the training progress in photoelectric feedback system

图9(a)中,真实的目标混沌序列和LSTM预测的混沌序列大部分都拟合在 $y=x$ 直线上,经计算预测 $RMSE = 5.500 \times 10^{-3}$ ,系统同步系数高达0.999 8,说明系统预测效果较好且具有高质量的混沌同步性。

由加密信息减去神经网络预测的混沌载波直接解调出的有噪信息如图9(b)所示,经计算,误码率BER为 $6.92 \times 10^{-13}$ ,说明系统具备高质量的混沌同步通信能力。经过量化解调后的信息如图9(c)所示,其与原始信息图7(b)几乎相同,系统通信质量较高。综合可见,LSTM神经网络结构同样适用于光电反馈混沌光通信系统。

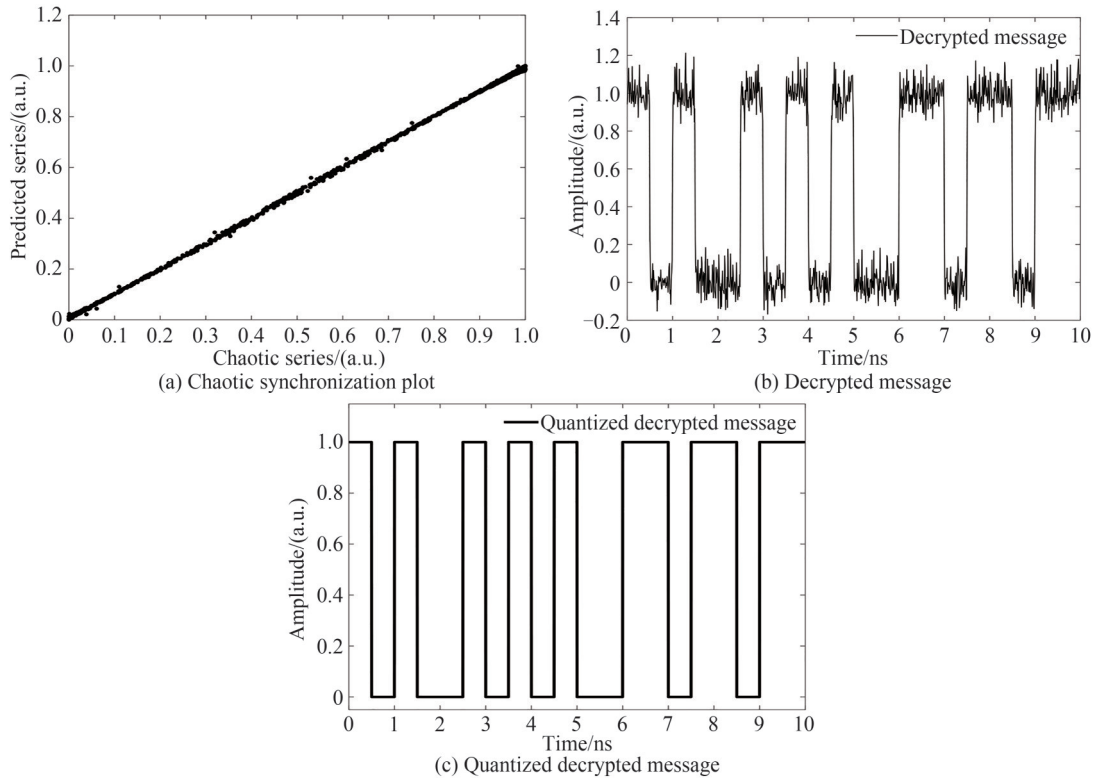


图9 光电反馈系统中接收端解密信息  
Fig.9 The decrypted message of receiver in photoelectric feedback system

### 3 系统性能分析

#### 3.1 同步系数与误码率分析

原始信息与混沌载波之间的耦合系数以及LSTM神经网络的节点数量是影响系统性能的重要因素,针对这些因素,在光反馈混沌系统下详细分析它们对于系统性能的影响。

保持耦合系数0.08,信噪比30 dB不变,节点数量在100~1 200之间,每隔100个节点对系统性能影响如图10所示。整体来看,同步系数和RMSE整体上呈现出相反的趋势,即当同步系数越大时,RMSE的值越小,反之亦然,这是由于随着目标载波与预测载波之间相似性的增强,两者之间的差距会越来越小。在节点数量较少时,系统能够表现出较好的BER性能,其值都能低至 $10^{-10}$ 量级,当节点数量为300时,同步系数达

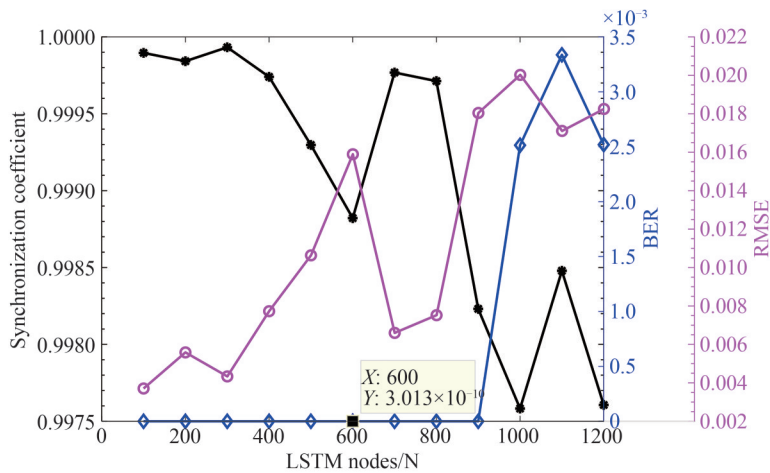


图10 LSTM节点对系统性能的影响  
Fig.10 Impact of the LSTM nodes on system performance



到峰值为0.999 93。当节点数量增加至1 000时,BER陡增至 $10^{-3}$ 量级,信息出现一定失真,此时由于系统节点过多,模型复杂度变得更高,出现LSTM模型在训练集上损失很小,但在验证和测试集上表现很差,此时系统呈现过拟合状态,导致LSTM模型不能精确预测混沌载波,解密出现一定失真。

图10所示的系统性能详细数据如表2所示。节点数量位于100至900之间时,系统同步系数都能达到0.998 2之上, RMSE低至 $10^{-2}$ 量级或之下, BER均低于 $10^{-10}$ 量级,系统具备较为优良的通信质量。

表2 图10中不同节点下的同步系数、BER和RMSE  
Table 2 The value of synchronization coefficient, BER and RMSE at different nodes in Fig. 10

LSTM nodes	100	200	300	400	500	600
Synchronization coefficient	0.999 90	0.999 84	0.999 93	0.999 74	0.999 30	0.998 82
BER	$1.11 \times 10^{-24}$	$3.28 \times 10^{-12}$	$1.04 \times 10^{-18}$	$1.65 \times 10^{-29}$	$2.60 \times 10^{-16}$	$3.01 \times 10^{-10}$
RMSE	$3.71 \times 10^{-3}$	$5.58 \times 10^{-3}$	$4.34 \times 10^{-3}$	$7.73 \times 10^{-3}$	$1.06 \times 10^{-2}$	$1.59 \times 10^{-2}$
LSTM nodes	700	800	900	1 000	1 100	1 200
Synchronization coefficient	0.999 77	0.999 71	0.998 23	0.997 58	0.998 48	0.997 61
BER	$1.96 \times 10^{-29}$	$2.43 \times 10^{-21}$	$5.36 \times 10^{-12}$	$2.51 \times 10^{-3}$	$3.33 \times 10^{-3}$	$2.52 \times 10^{-3}$
RMSE	$6.60 \times 10^{-3}$	$7.52 \times 10^{-3}$	$1.80 \times 10^{-2}$	$2.00 \times 10^{-2}$	$1.71 \times 10^{-2}$	$1.83 \times 10^{-2}$

由表2发现,系统节点数较少时仍能获得较高的同步系数和较低的误码率,因此进一步研究了节点位于40~240区间对于系统性能的影响。由表3数值发现,在少节点情况下,系统同步系数均达到0.999 8以上, BER均低于 $10^{-8}$ 量级,远低于硬判决前向纠错阈值标准值 $3.8 \times 10^{-3}$ 。当网络节点数量为240时,同步系数取得最大值为0.999 96。在基于LSTM的混沌同步通信系统中,少节点与多节点状态所获得的系统性能差不多的情况下,选择少节点状态,可以极大降低时间损耗,节约训练神经网络的时间成本。

表3 少节点对系统性能的影响  
Table 3 The impact of the slight nodes on system performance

LSTM nodes	40	80	120	160	200	240
Synchronization coefficient	0.999 94	0.999 92	0.999 89	0.999 93	0.999 93	0.999 96
BER	$3.49 \times 10^{-8}$	$2.84 \times 10^{-24}$	$3.96 \times 10^{-15}$	$3.31 \times 10^{-31}$	$9.65 \times 10^{-21}$	$6.89 \times 10^{-9}$
RMSE	$7.23 \times 10^{-3}$	$3.71 \times 10^{-3}$	$4.99 \times 10^{-3}$	$3.18 \times 10^{-3}$	$4.03 \times 10^{-3}$	$6.82 \times 10^{-3}$

保持网络节点200,信噪比30 dB不变,耦合系数在0.02~0.12之间每隔0.01对系统性能影响如图11所示。整体来看,同步系数和RMSE仍呈现出相反的趋势。随着耦合系数的增大,信息误码率均远低于 $3.8 \times 10^{-3}$ ,系统具备极高的通信质量。

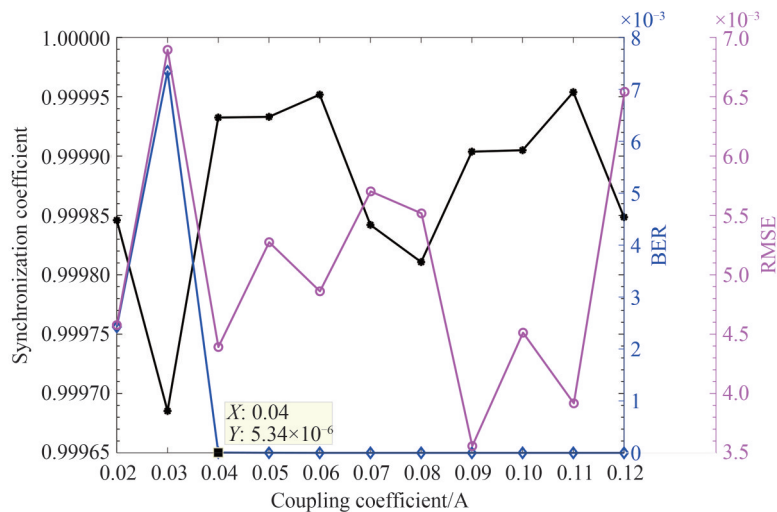


图11 耦合系数对系统性能的影响

Fig.11 Impact of the coupling coefficient on system performance

图 11 系统性能详细数据如表 4 所示。系统同步系数都能达到 0.999 0 之上, RMSE 低至  $10^{-3}$  量级, 当耦合系数达到 0.04 时, 误码率达到较低水平, 系统通信质量较好。

表 4 图 11 中不同耦合系数下的同步系数、BER 和 RMSE

Table 4 The value of synchronization coefficient, BER and RMSE at different coupling coefficient in Fig. 11

Coupling coefficient	0.02	0.03	0.04	0.05	0.06	0.07
Synchronization coefficient	0.999 85	0.999 69	0.999 93	0.999 95	0.999 95	0.999 84
BER	$2.42 \times 10^{-3}$	$7.35 \times 10^{-3}$	$5.34 \times 10^{-6}$	$1.77 \times 10^{-6}$	$1.15 \times 10^{-9}$	$1.42 \times 10^{-9}$
RMSE	$4.58 \times 10^{-3}$	$6.89 \times 10^{-3}$	$4.39 \times 10^{-3}$	$5.27 \times 10^{-3}$	$4.86 \times 10^{-3}$	$5.70 \times 10^{-3}$
Coupling coefficient	0.08	0.09	0.10	0.11	0.12	
Synchronization coefficient	0.999 81	0.999 90	0.999 90	0.999 95	0.999 85	
BER	$4.55 \times 10^{-14}$	$5.94 \times 10^{-31}$	$2.04 \times 10^{-25}$	$6.26 \times 10^{-36}$	$1.61 \times 10^{-18}$	
RMSE	$5.52 \times 10^{-3}$	$3.56 \times 10^{-3}$	$4.51 \times 10^{-3}$	$3.92 \times 10^{-3}$	$6.54 \times 10^{-3}$	

考虑到通信过程中, 信号可能会受到不同程度的链路损伤以及噪声干扰, 因此通过不同水平的信噪比来分析 LSTM 网络模型的泛化性。保持网络节点 200, 耦合系数 0.08, 信噪比在 5~40 dB 之间, 每隔 5 dB 对系统性能影响如图 12 所示。由图 12 可见, 系统同步系数均能达到 0.999 8 以上, 然而由于同步系数本身已经达到较高水平, 上升空间很小, 所以图中显示同步系数在 0.999 9 附近上下波动, LSTM 网络具有极其精准的预测能力。信噪比在 10 dB 及以下时, 有噪声信息本身就已经强烈失真, 在未对有噪声信息进行滤波处理情况下, 纵使载波同步系数高, 解密恢复出的信息仍处于失真状态。当信噪比达到 15 dB 时, BER 达到  $10^{-6}$  量级, 远低于 HDFEC。当信噪比为 25 dB 时, 同步系数达到峰值, 其值为 0.999 966。总的来看, 信噪比达到 15 dB 后, 系统误码率均远低于硬判决前向纠错阈值标准, 达到理想的通信标准, 同时随信噪比的升高而降低。

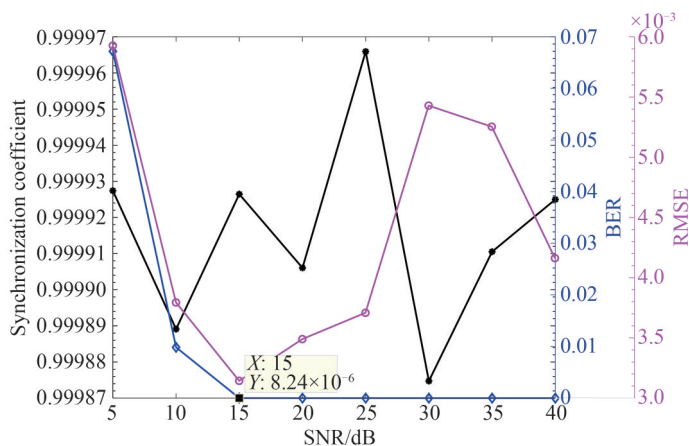


图 12 信噪比对系统性能的影响

Fig.12 Impact of the SNR on system performance

### 3.2 系统安全性分析

安全性是混沌通信过程中的重要因素, 从暴力搜索、明文攻击和密文攻击三方面对其进行分析。针对暴力搜索攻击方面, 首先神经网络具有 200 个节点, 理论上节点有无数种组合方式, 使得神经网络本身就具备十分庞大的参数空间。其次神经网络所需要训练的参数能够达到四千之多, 每个参数取值均不受限制, 这进一步扩大了神经网络的参数空间。因此, 很难通过暴力搜索的方式来匹配如此多的参数并获得类似的神经网络。针对密文攻击, 在窃听者获取加密信号的情况下, 由于没有正确的目标载波作为神经网络的输出, 所以窃听者无法进行损失函数的计算以及网络参数的更新。针对明文攻击, 在攻击者通过一定手段窃取加密信号和部分明文的情况下, 攻击者可以选择利用两道信号训练神经网络, 但是本文 LSTM 系统线下需要大量的混沌载波信号对网络进行优化, 其次, 攻击者所获取的加密信号和部分明文只是信道传输过程中的任意一部分, 两者本身就很难正确匹配。因此, 攻击者并不能通过训练得到正确的神经网络。综合看来, 基于 LSTM 的混沌同步通信系统能够抵御众多攻击, 具有极高的安全性。

### 3.3 仿真实验验证与分析

为了验证系统的实际可用性,以 $256 \times 256$ 像素的灰度图为例,在光反馈系统中利用神经网络结构对图像进行传输并分析了噪声对信号传输的影响。同时考虑到中值滤波作为图像处理中的一种非线性数字滤波技术,它会规律性选取图像中的像素点及其周边一定区域内的像素值,将像素值依次排序后,最终会用中间位置的像素值来代替当前的像素值,具有消除孤立噪声点,保护图像边缘信息的作用,因此将其用于图像噪声处理过程中。

图13中(a)为未添加噪声的原始图像,(b)为加密图,(c)为直接解密图,(d)为经过中值滤波后的解密图;(e)为添加了均值为0,方差为0.01高斯噪声后的图像,(f)为添加高斯噪声后的加密图,(g)为添加高斯噪声后的解密图,(h)是对具有高斯噪声的图像进行中值滤波后的解密图;(i)为添加了噪声密度为0.05的椒盐噪声后的图像,(j)为添加椒盐噪声后的加密图,(k)为添加椒盐噪声后的解密图,(l)是对具有椒盐噪声的图像进行中值滤波后的解密图。观察图13(b)、(f)、(j),可以发现图像可以有效隐藏在混沌载波中,由(c)、(g)、(k)可知,解密出的图像由于噪声的原因,变得不平滑,在经过中值滤波处理后,如(d)、(h)、(l),图像变得平滑但同时清晰度也有些许降低。不过观察图13(k)和(l),可以发现中值滤波十分适合处理椒盐噪声,这是由于椒盐噪声是因信号脉冲强度引起的随机孤立的黑白像素点,而中值滤波具有消除周围孤立噪声点的功能,因此可以完美消除椒盐噪声,有效保护图像的边缘信息。整体来看,该系统成功对图像进行了传输和加解密操作,系统的安全性和通信质量都得到一定的保障。

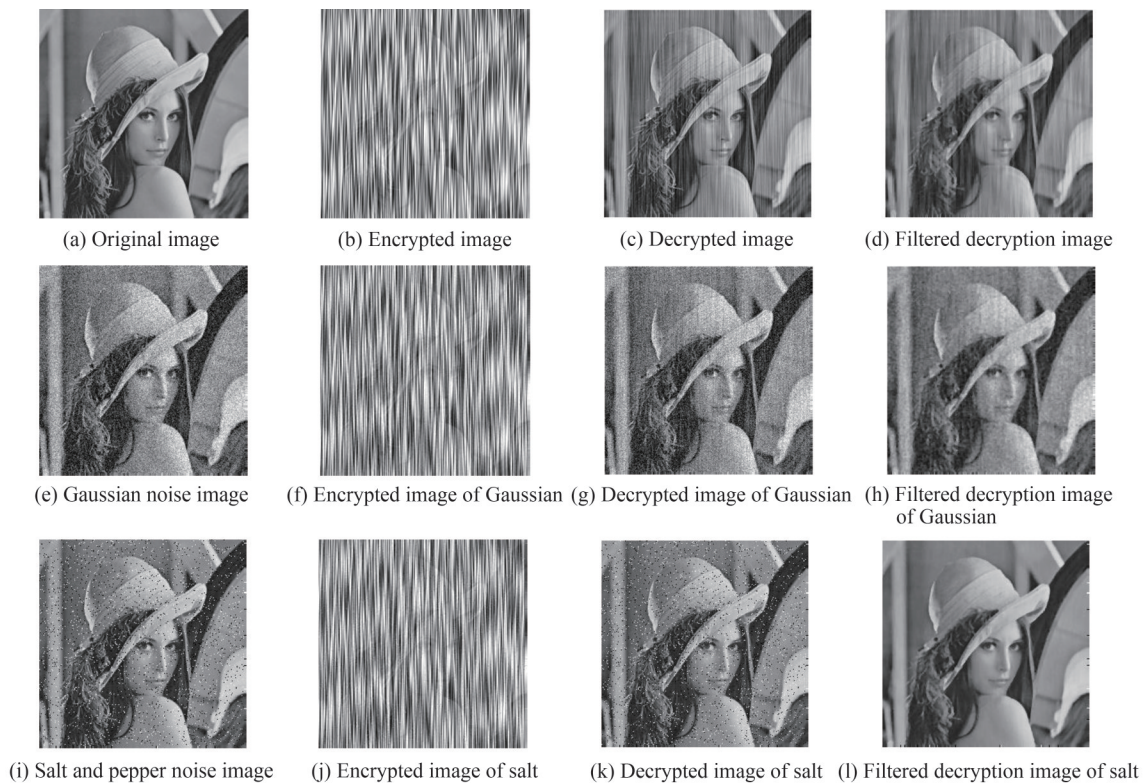


图13 高斯噪声和椒盐噪声对系统图像传输的影响

Fig.13 The effect of Gaussian noise and salt and pepper noise on system image transmission

## 4 结论

本文提出的基于LSTM神经网络的激光混沌同步通信,利用大量数据对网络进行了训练,使其可以完美替代混沌通信接收端,在光反馈和光电振荡器系统中都实现了高质量的混沌同步通信。当LSTM节点较多或者耦合系数较低时,解密信息会出现一定失真。通过对图像进行传输,进一步验证了本方案的可行性。在接收端使用LSTM模型恢复混沌载波,同步系数最高可达0.999 966,误码率BER低至 $10^{-10}$ 量级,实现了高质量的混沌同步通信。本方案的优势在于:1) LSTM凭借其学习时间序列长期依赖关系以及强鲁棒性的



特质,使得本方案在光反馈和光电反馈系统中均实现了较高质量的同步通信,具有一定的通用性;2) 基于 LSTM 的混沌同步通信系统中,少节点与多节点状态所获得的系统性能都很突出,选择少节点状态,可以极大降低时间损耗,节约训练神经网络的时间成本;3) 提出的 LSTM 方案成功解决了传统混沌光通信中接收双方硬件参数匹配困难的问题,同时具有便捷性和安全性,可为后续混沌光通信研究提供思路。

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## Laser Chaotic Synchronization Communication Based on LSTM

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**Abstract:** Laser chaotic communication system is widely used in the field of secure communication due to its unique advantages such as strong randomness, quasi-noise, and high bandwidth of chaotic signals. At present, laser chaotic synchronization communication generally depends on the laser internal nonlinear effect or photoelectric oscillator. Still, it is difficult to achieve high-quality synchronization communication because of the difficulty of hardware parameters matching between the transmitter and the receiver. Aiming at this shortcoming, some scholars have proposed to use the powerful nonlinear fitting ability of a neural network to model the receiver of a chaotic optical communication system, to realize high-quality synchronization communication. This paper proposes to use the long short-term memory neural network for the mathematical modeling of the chaotic optical transmitter. It successfully solves the problems of complex hardware systems and low synchronization coefficients in traditional chaotic optical communication and provides a reference for point-to-multipoint chaotic communication.

This paper presents the design of a laser chaotic synchronization communication system based on long short-term memory neural network, and uses a cross-prediction algorithm to optimize the network model. In the off-line training stage, a large number of chaotic encrypted signals generated by the transmitter are used as input variables of the neural network, and the real chaotic carrier sequence is further selected by the cross-prediction algorithm as output variables of the neural network. To enable the long short-term memory neural network to accurately predict the output variables according to the input variables, each training iteration of the network will update its node state until the ideal loss value is reached. In the test stage, the node state of the neural network has been determined. When the input variable is received, the system will automatically map the predicted carrier sequence, and the received encrypted signal can be directly subtracted from the predicted carrier sequence to decrypt useful information. The scheme achieves a high synchronization coefficient and achieves high-quality chaotic synchronization communication.

The simulation result consists of three parts. The first is the quality of decrypted information at the receiver end. After modeling and training of laser chaotic system by long short-term memory neural network, the system has good prediction effect and high-quality chaotic synchronization. The synchronization coefficient between the real target carrier and the predicted carrier is more than 99.9%, and the root means the square error is as low as  $10^{-3}$ . The noisy information is demodulated directly from the encrypted information minus the chaotic carrier predicted by the neural network, and the bit error rate is as low as  $10^{-10}$ . It is far lower than the hard decision threshold of the forward error correlation standard, which

is  $3.8 \times 10^{-3}$ . To verify the universality of the system, the simulation of optical feedback and photoelectric feedback synchronization communication system has the same level of communication quality. Secondly, the influence of the number of network nodes, the information coupling coefficient, and the signal-to-noise ratio on the chaotic synchronization communication performance is studied in the optical feedback chaotic synchronization communication system. The results show that when the coupling coefficient is 0.08, the signal-to-noise ratio is 30 dB unchanged, and the number of nodes is between 200 and 800, the system has good bit error rate performance, and the maximum is only  $10^{-10}$ . When the number of nodes is 300, the synchronization coefficient reaches the peak value of 0.999 93. When the number of nodes reaches 1 000~1 200, the neural network appears overfitting state, and the information appears with certain distortion. This paper further studies the effect of nodes in the range of 40~240 on system performance. In the case of a few nodes, the synchronization coefficients of the system are all above 0.999 8, the bit error rate is far lower than the hard decision threshold of forward error correlations standard, and the bit error rate is lower than  $10^{-8}$  magnitude. When the number of network nodes is 240, the maximum synchronization coefficient is 0.999 96. For the coupling coefficient, the number of nodes is kept at 200 and the signal-to-noise ratio is unchanged at 30 dB. When the coupling coefficient is large and reaches 0.04~0.12, the bit error rate of the system can reach a relatively low level stably, all of which are lower than  $10^{-6}$ , and the system communication quality is good. At the same time, when the coupling coefficient reaches 0.11, the maximum synchronization coefficient of the system is 0.999 95. For the signal-to-noise ratio, keep the network nodes 200, the coupling coefficient 0.08 unchanged, the signal-to-noise ratio between 5~40 dB, and the system synchronization coefficient can reach above 0.999 8. When the signal-to-noise ratio reaches 15 dB, the bit error rate reaches the order of  $10^{-6}$ , far lower than the hard decision threshold of the forward error correlations standard. When the signal-to-noise ratio is 25 dB, the synchronization coefficient reaches the peak value, which is 0.999 966. Finally, to verify the actual availability of the system, the grayscale image of  $256 \times 256$  is successfully transmitted in the optical feedback system. In addition, the system security is analyzed from three aspects: brute force search, plaintext attack, and ciphertext attack. The results show that the system can resist many attacks and has high security.

The proposed laser chaotic synchronization communication based on long short-term memory neural network and the network structure optimization by cross-prediction algorithm achieves high-quality chaotic synchronization communication in both optical feedback and photoelectric oscillator system. This scheme successfully solves the problems of complex hardware systems and low synchronization coefficients in traditional chaotic optical communication. Then, the influence of long short-term memory neural network nodes, coupling coefficient, and signal-to-noise ratio on the communication performance of the system is studied. When there are more nodes or the coupling coefficient is low, the decryption information will appear with a certain distortion. Finally, the feasibility of this scheme is further verified by image transmission. As a whole, the synchronization coefficient of the system can be as high as 0.999 966, and the bit error rate is as low as  $10^{-10}$ , which realizes high-quality chaotic synchronization communication. The advantages of this scheme are as follows. First, long short-term memory neural network, with its long-term dependence on learning time series and strong robustness, enables this scheme to achieve high-quality synchronous communication in both optical feedback and photoelectric feedback systems and has certain universality. Second, in the chaotic synchronous communication system based on long short-term memory neural network in this paper, the system performance obtained by the state of a few nodes and multiple nodes is outstanding. Choosing the state of a few nodes can greatly reduce the time loss and save the time cost of training neural networks. Third, the long short-term memory neural network scheme proposed in this paper successfully solves the problem of hardware parameter matching between the two receivers in traditional chaotic optical communication and has the advantages of convenience and security, which provides a thought for the subsequent research of chaotic optical communication.

**Key words:** Laser communication; Chaos synchronization; Long short-term memory neural networks; Optical feedback; Optoelectronic feedback; Chaotic prediction

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