Efficient Video Processing Schemes for Compression and Security

Abstract

This thesis addresses the important challenges of video encryption, compression, and high-quality recovery through a series of novel methods based on chaos theory and deep learning. We develop robust, compression-independent video encryption systems operating at both the frame and shot levels in the first set of contributions. Using a logistic sine coupling map to create a pseudorandom chaotic sequence for block-level diffusion, a frame-level strategy presents a novel confusion mechanism based on sort index permutation and thus improves robustness against known and chosen plaintext attacks. Complementarily, a shot-level approach exploits temporal redundancy to derive sparse difference frames, and it uses a newly proposed logistic tent infinite collapse map (LT-ICM) to both permute and substitute pixel values effectively, ensuring rapid encryption with enhanced security and efficiency. Building on this foundation, the thesis also investigates video Compressive Sensing (CS) techniques based on deep learning that are intended for use in cloud-based surveillance and telemedicine. To optimize sampling process and recover high-quality video data, videos are divided into Groups of Pictures (GOPs) that comprise both keyframes and non-keyframes. A convolutional neural network (CNN) with a loss function based on the Structural Similarity Index Measure (SSIM) is then used. The recovery process utilises an initial spatial reconstruction stage followed by a deep recovery stage that implements multilevel and single-level feature compensation to effectively restore non-keyframes using contextual information from both keyframes and neighboring non-keyframes. A joint compression and encryption approach is developed, using Parallel Compressive Sensing (PCS) in combination with improved chaotic maps. This method analyses video in GOP segments, applying DCT-based sparsification to reference frames and then permuting coefficients, while the measurement matrix is produced using a one-dimensional LT-ICM. We introduce a novel substitution method that utilises circular shift, XOR, and modular addition operations. We finally shuffle the substituted frames using a frame-dependent two-dimensional

LT-ICM chaotic sequence. Experimental analysis, including comparisons with state-of-the-art approaches, establishes the effectiveness of the proposed solution. We propose a secure, high-quality video recovery framework that seamlessly integrates deep learning-based compressed sensing (CS) with an advanced encryption strategy. This scheme not only capitalises on the superior recovery capabilities of the CNN-based two-stage process but also reinforces data security through a multi-phase encryption routine (forward diffusion, substitution, backward diffusion, and XORing) powered by an unpredictably complex Sine Symbolic Chaotic Map (SSCM). Comprehensive experimental analyses across all methods demonstrate significant improvements in encryption speed, correlation robustness, entropy measures, and overall reconstruction quality, thereby outperforming several state-of-the-art techniques. Finally, an adaptive shot-level unified framework is proposed by integrating adaptive parallel compressive sensing (APCS) with a secure encryption pipeline. In this framework, shot boundaries are first detected, followed by adaptive sampling within each shot. A highly unpredictable one-dimensional chaotic map Log–Logistic–Cubic (LLC) is used for both measurement matrix generation and encryption operations, while the matrices are further optimized through QR decomposition with Givens rotations to enhance reconstruction quality. Overall, the proposed framework achieves an effective balance between compression efficiency, low-sampling-ratio recovery, and video security. Collectively, the contributions of this thesis establish innovative paradigms for secure and efficient video processing, paving the way for reliable applications in environments demanding high security.