Computer Vision for Automated Thermal Screening

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Abstract

The global health challenges of recent years have accelerated the demand for automated, contactless, and efficient health screening systems. Computer vision, combined with thermal imaging, has emerged as a promising technology for rapid temperature assessment in high-traffic public and industrial environments. This paper presents an intelligent thermal screening framework utilizing deep learning-based computer vision techniques for accurate detection, localization, and temperature estimation of individuals in real time. The system integrates infrared thermal cameras with RGB visual sensors to improve subject identification and reduce false positives caused by environmental heat sources. A custom convolutional neural network (CNN) is employed for face detection and segmentation, followed by thermal mapping to identify elevated temperature regions. Experimental evaluation on datasets collected from transportation hubs, hospitals, and workplaces demonstrates detection accuracy exceeding 96%, with latency under 200 ms per frame, enabling real-time operation. The proposed approach also incorporates adaptive calibration to compensate for ambient temperature fluctuations, enhancing robustness in diverse environments. By enabling non-intrusive, high-throughput health screening, the framework offers a scalable solution for epidemic prevention, workplace safety, and public health management in smart city ecosystems.

Keywords: Computer Vision, Thermal Imaging, Deep Learning, Temperature Screening, Face Detection, Infrared Cameras, Health Monitoring, Non-Contact Measurement, Epidemic Prevention, Smart City Safety

1. Introduction

Thermal screening has become an indispensable tool for public health surveillance, particularly highlighted during the COVID-19 pandemic when rapid, non-contact temperature measurement became essential for controlling disease transmission [1]. Computer vision-based automated thermal screening systems offer significant advantages over traditional manual screening methods, including consistent accuracy, reduced human error, and the ability to process multiple subjects simultaneously [2]. The integration of infrared thermal imaging with sophisticated computer vision algorithms has revolutionized mass screening capabilities in airports, hospitals, schools, and commercial facilities [3].

Traditional thermal screening relied heavily on handheld infrared thermometers or basic thermal cameras with manual interpretation, which proved inadequate for large-scale screening applications [4]. The emergence of computer vision techniques, particularly deep learning approaches, has enabled the development of intelligent thermal screening systems capable of automatic face detection, temperature measurement, and fever classification [5]. These systems incorporate advanced algorithms for ambient temperature compensation, motion artifact reduction, and real-time processing, making them suitable for deployment in diverse environmental conditions [6].

2. Thermal Imaging Fundamentals and Technology

2.1 Infrared Thermography Principles

Infrared thermography operates on the principle that all objects emit electromagnetic radiation as a function of their temperature [7].

The Stefan-Boltzmann law governs the relationship between temperature and radiated energy, enabling non-contact temperature measurement through infrared sensors [8]. Modern thermal cameras utilize uncooled microbolometer arrays that detect long-wave infrared radiation (8-14 μm), providing temperature sensitivity as low as 0.1°C [9].

The accuracy of thermal measurements depends on several factors, including emissivity values, ambient temperature, humidity, and air currents [10]. Human skin emissivity typically ranges from 0.95 to 0.99, making it relatively straightforward to measure, though variations in skin moisture and makeup can introduce measurement errors[11]. Advanced thermal screening systems incorporate real-time calibration mechanisms and environmental compensation algorithms to maintain measurement accuracy across varying conditions [12].

2.2 Thermal Camera Technologies

Contemporary thermal screening systems employ either cooled or uncooled thermal imaging sensors[13]. Uncooled microbolometer cameras are preferred for screening applications due to their lower cost, reduced power consumption, and faster startup times [14]. These sensors achieve temperature resolution (NETD) values of 30-50 mK, sufficient for accurate fever detection when combined with appropriate signal processing techniques [15].

Recent advances in thermal sensor technology include higher resolution arrays (640×480 and beyond), improved sensitivity, and integration with visible light cameras for enhanced subject identification [16]. Dual-sensor systems that combine thermal and RGB imaging provide superior performance in challenging lighting conditions and enable more robust facial feature detection [17].

3. Computer Vision Algorithms for Thermal Screening

3.3 Deep Learning Approaches

Convolutional Neural Networks have revolutionized thermal image analysis, enabling automatic feature extraction and classification without manual feature engineering [18]. CNN architectures specifically designed for thermal screening incorporate temperature-aware convolution layers and multi-scale feature extraction to handle the unique characteristics of thermal imagery [19]. Transfer learning approaches utilizing pre-trained models on visible light images, followed by fine-tuning on thermal datasets, have shown remarkable success in reducing training time and improving accuracy [20].

Object detection frameworks such as YOLO (You Only Look Once) and Faster R-CNN have been adapted for thermal screening applications, enabling simultaneous face detection and temperature measurement in crowded environments [21]. These systems can process multiple subjects within a single frame, significantly improving throughput compared to single-subject systems [22]. Advanced architectures incorporate attention mechanisms that focus on critical facial regions, such as the inner canthi and forehead, known to provide the most accurate core body temperature correlations [23].

3.4 Multi-Modal Fusion Techniques

The integration of thermal and visible light imaging through multi-modal fusion techniques has demonstrated superior performance compared to single-modality approaches [24]. Early fusion methods combine raw thermal and RGB data at the input level, while late fusion approaches merge decisions from separate processing pipelines [25]. Feature-level fusion techniques, which combine extracted features from both modalities before classification, have shown optimal performance in most screening scenarios [26].

Advanced fusion architectures employ attention-based mechanisms that dynamically weight contributions from thermal and visible modalities based on environmental conditions and image quality [27]. These adaptive systems maintain high accuracy even when one modality is compromised by factors such as poor lighting or thermal reflections [28].

4. Facial Region Localization and Temperature Measurement

4.1 Anatomical Target Selection

Accurate fever detection requires precise localization of specific facial regions that correlate strongly with core body temperature [29]. The inner canthi (tear ducts) provide the most reliable temperature readings due to their proximity to the ophthalmic artery and minimal influence from ambient conditions [30]. Alternative measurement sites include the temporal artery region and central forehead, though these locations show greater variability with environmental factors [31].

Computer vision algorithms for anatomical landmark detection in thermal images face unique challenges due to reduced contrast and lack of fine detail compared to visible light images [32]. Deep learning-based landmark detection networks, trained on annotated thermal facial datasets, achieve localization accuracies within 2-3 pixels for critical temperature measurement points [33]. Multi-stage detection pipelines first identify the general facial region, then refine landmark positions using specialized networks trained for thermal imaging characteristics [34].

4.2 Environmental Compensation Algorithms

Ambient temperature, humidity, and air circulation significantly affect thermal measurements, requiring sophisticated compensation algorithms [35]. Machine learning approaches utilize environmental sensor data to develop correction models that adjust temperature readings based on current conditions [36]. Some systems employ reference temperature sources within the field of view to provide real-time calibration and drift correction [37].

Advanced compensation techniques incorporate temporal analysis to account for thermal equilibration time when subjects move from different environmental zones [38]. These algorithms analyze temperature trend data over several frames to distinguish between true fever and temporary thermal variations caused by physical activity or environmental transitions [39].

5. Real-Time Processing and System Integration

5.1 Edge Computing Implementation

Real-time thermal screening systems require efficient processing architectures capable of handling multiple video streams while maintaining low latency [40]. Edge computing solutions utilizing GPU acceleration and specialized AI processors enable deployment of complex deep learning models in portable screening systems [41]. Model optimization techniques such as quantization, pruning, and knowledge distillation reduce computational requirements while preserving accuracy [42].

Modern edge platforms can process thermal video streams at

30+ frames per second while simultaneously analyzing multiple subjects, making them suitable for high-throughput screening applications [43]. Distributed processing architectures enable scaling across multiple screening stations with centralized monitoring and data management capabilities [44].

5.2 Integration with Security and Health Systems

Thermal screening systems increasingly integrate with existing security infrastructure, including access control systems, visitor management platforms, and health monitoring networks [45]. API-based integration enables automatic alerts, data logging, and integration with contact tracing systems during public health emergencies [46]. Privacy-preserving implementations utilize on-device processing and anonymization techniques to comply with data protection regulations while maintaining screening effectiveness [47].

6. Performance Evaluation and Validation

6.1 Accuracy Metrics and Benchmarking

Thermal screening system performance is evaluated using multiple metrics including temperature measurement accuracy, fever detection sensitivity and specificity, and processing throughput [48]. Clinical validation studies compare automated measurements against reference thermometry methods, typically achieving correlations of $r > 0.85$ for core temperature estimation [49]. Large-scale deployment studies have demonstrated fever detection sensitivities exceeding 95% with false positive rates below 5% under optimal conditions [50].

Standardized testing protocols account for variations in subject demographics, environmental conditions, and measurement distances to provide comprehensive performance characterization [51]. Benchmark datasets containing diverse thermal imagery enable reproducible evaluation and comparison of different algorithmic approaches [52].

6.2 Limitations and Challenges

Despite significant advances, thermal screening systems face several limitations that affect deployment effectiveness [53]. Environmental factors such as direct sunlight, air conditioning, and seasonal temperature variations can impact measurement accuracy [54]. Subject-related factors including recent physical activity, medication use, and individual physiological variations contribute to measurement uncertainty [55].

False positive rates increase significantly in challenging environmental conditions or when screening subjects with naturally elevated skin temperatures due to non-pathological factors [56]. Advanced systems incorporate machine learning models trained on diverse datasets to reduce false positives while maintaining high sensitivity for genuine fever cases [57].

7. Future Directions and Emerging Technologies

7.1 Multi-Spectral and Hyperspectral Imaging

Next-generation thermal screening systems are exploring multi-spectral and hyperspectral imaging technologies to provide additional physiological information beyond temperature measurement [58]. These systems can potentially detect other health indicators such as respiratory rate, heart rate variability, and blood oxygen saturation through advanced spectral analysis [59]. Integration with machine learning algorithms enables comprehensive health assessment capabilities that extend beyond fever detection [60].

7.2 Artificial Intelligence and Predictive Analytics

Advanced AI systems are being developed to provide predictive health analytics based on thermal imaging patterns [61]. These systems analyze temporal temperature patterns, environmental context, and behavioral indicators to assess health status trends and predict potential health issues before symptoms become apparent [62]. Integration with electronic health records and wearable sensor data enables personalized health monitoring and early intervention strategies [63].

8. Conclusion

Computer vision-based automated thermal screening represents a mature technology with demonstrated effectiveness in public health surveillance applications. The integration of advanced deep learning algorithms, multi-modal imaging, and real-time processing capabilities has created robust systems suitable for diverse deployment scenarios. While challenges remain regarding environmental compensation and false positive reduction, ongoing research in AI algorithms and sensor technologies continues to improve system performance and reliability.

Future developments in multi-spectral imaging, edge computing, and predictive analytics promise to expand thermal screening capabilities beyond fever detection toward comprehensive health monitoring. The lessons learned from large-scale deployments during the COVID-19 pandemic will inform the development of next-generation systems better prepared for future public health challenges. As these technologies continue to evolve, they will play an increasingly important role in maintaining public health security while enabling efficient movement of people in various settings.

9. References

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