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Multi-sensor Fusion Methods for Environment Perception in Smart Homes

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Abstract:

Currently, smart home technology is a highly popular research field, encompassing the application of advanced sensors and the development of sophisticated algorithms. Among these, multi-sensor fusion stands out as a critical direction, playing a pivotal role in enhancing various aspects of smart home systems by integrating data from multiple sensors for improved environmental perception and decision-making. However, despite its significance, there is a lack of comprehensive review studies summarizing the progress and challenges in this area of multi-sensor fusion within the context of smart home technology.This field lacks the organization and induction of the underlying framework. This article organizes the content of multi-sensor fusion and links it with the smart home to make the basic concepts more vivid. While systematically organizing the relevant concepts, it partially extends the fields of robotics and control and proposes the possibility of combining multi-sensor fusion technology with smart home. By introducing algorithms and concepts to quickly understand the importance of multi-sensor fusion in smart home, the paper provides a basic manual for those who are just starting to study this field or those who are interested in this field.

Keywords: Multi-sensor fusion, Smart home, Environmental perception

1. Introduction

The smart home is a relatively broad concept that includes indoor temperature control systems and smart nanny robots. With the aging population and the increase in life pressure, smart homes have a broad market as lubricants. No matter what kind of smart home it is, its most important ability is environmental perception or indoor positioning. Environmental perception techniques are varied and extensive, with options like inertial navigation, Wi-Fi, Bluetooth technology, radio-frequency identification (RFID), ultra-wideband (UWB), odometer readings, ultrasonic methods, and LiDAR-based positioning, tailored to meet different application requirements. However, it is difficult to effectively integrate information between different sensors, and the problems of delay and stability have always been complex to solve[1].

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Due to the difficulty in altering the error characteristics of different sensors, various multi-sensor fusion methods have been developed, particularly those that leverage the distinct characteristics of IMU and other sensors[2] [3] [4]. The main goal of multi-sensor fusion involves improving the system's capacity for detecting and adapting to environmental changes by combining data from multiple sensors. In smart homes, this integration enhances the precision and dependability of environmental monitoring, minimizes system uncertainty, and optimizes decision-making processes.

The effectiveness of multi-sensor fusion depends on how data is integrated and processed, which is generally categorized into three main stages: data-layer, feature-layer, and decision-layer fusion. Each fusion level plays a unique role in processing sensor data, from combining raw data at the data layer to extracting abstract features at the feature layer and refining decisions at the decision layer. In smart home systems, these various fusion stages enhance the system's ability to gain a deeper and more precise insight into the home setting, facilitating improved automation and control. Currently, the latest research on multi-sensor fusion primarily emphasizes algorithm enhancements, but offers limited detailed explanations on the ways it improves the performance of control systems, particularly in smart home applications. This article systematically reviews the foundational principles of multi-sensor fusion, specifically linking these concepts to the widely discussed area of smart home technologies. It also puts forward hypotheses on possible research directions in the future, aiming to serve as the foundation for research work and provide theoretical help for researchers in this field.

The article first presents the theoretical underpinnings of how multi-sensor fusion can enhance smart home environment perception. Then, it details what kind of improvement can be achieved through the data, feature, and decision layers, how to achieve these improvements, and what limitations there are. Then, combined with some of the latest research, it looks forward to possible research directions in the future.

2. Theoretical Foundation

Smart home refers to furniture automation devices that can be connected to the Internet and the environmental perception is an important part of smart home system. Sensors that need to be used include light sensors for adjusting indoor lighting, motion sensors for security monitoring or automation, and air quality sensors for detecting carbon dioxide concentration to control ventilation systems. The information a single sensor can provide is very limited and its output will be affected by its own quality and position. As a result, many indoor devices are typically equipped with numerous types of sensors to fulfill the requirements for detection and data collection. If the information collected by sensors is processed separately and in isolation, not only will the workload of information processing be greatly increased, but it will also be equivalent to giving up on building the internal connections between sensors, losing the environmental characteristics that may be contained after the information is organically combined, resulting in information waste and even decision-making errors.

To address these challenges, multi-sensor fusion is employed to enhance the exchange of information between sensors, thereby boosting the system's robustness and improving the accuracy of smart home operations. By leveraging data from various sensors, the system can minimize uncertainty in location estimation, resulting in more reliable and precise outcomes[5]. Through multi-sensor fusion in a room, the system can collect data from multiple spatial locations and from different perspectives. The indoor system can thus form a global perception of the entire room environment and avoid regional system deviations. In addition to improving the accuracy of environmental perception, it also helps in the fault tolerance of the system. At home, sensors may generate abnormal data due to environmental factors such as overheating, overhumidity, or failure over time. However, after the sensor data is integrated, even if one or more sensors fail, the system can still rely on the data of other normally operating sensors or make timely compensation for abnormal sensor output to achieve normal operation. The fused data after efficient integration of multi-source data can also provide high-quality training samples for machine learning and artificial intelligence algorithms. Through long-term data accumulation, the smart home system will be able to automatically adjust the environment according to user preferences.

3. Fusion Algorithm

Since various fusion strategies are applied at different levels of data abstraction, a range of fusion algorithms are utilized in multi-sensor data fusion. We categorize the fusion techniques employed in different research works to illustrate the fusion approaches adopted in these studies[6]. Structurally, multi-sensor fusion is divided into three levels according to the degree of abstraction of information processing in the fusion system: data layer fusion, feature layer fusion and decision layer fusion. In smart home systems, these various fusion levels help provide a deeper and more precise insight into the home environment, thereby enabling improved automation and control.

3.1 Data layer fusion

The term „data fusion" refers to the comprehensive process of combining data to improve state estimates and prediction accuracy. This approach offers the benefit of generating more consistent and precise information compared to relying on individual data sources[7]. Fusion strategy based on discernible unit. Initially, sensor observation data is merged, after which key features are derived from the fused dataset, followed by performing judgment and recognition, as depicted in Fig. 1. For some key sensors (such as temperature and humidity), different weights can be assigned to each sensor feature and fused based on the weighted average method. The formula is defined as

$$F = \frac{\sum_{i=1}^{n} w_i F_i}{\sum_{i=1}^{n} w_i}$$

There are various types of data fusion algorithms, but the most widely used ones are analytics-based techniques and learning-based techniques[8]. An analytics-driven approach uses mathematical techniques to represent system conditions and observations, often referred to as ‚estimations' in academic references[9]. Various analytics-based methods, like the Kalman Filter (KF) and Particle Filter (PF), are commonly utilized. Additionally, several learning-based data fusion techniques, such as Artificial Neural Networks (ANN), Fuzzy Logic, and Support Vector Machines (SVM), are also applied, as they have the ability to model systems without requiring prior statistical information about process and measurement noise[8]. In practical applications, by fusing data from multiple temperature and humidity sensors indoors, the system can better understand the indoor environment and optimize comfort. The location of the sensor may affect the accuracy of the data. For example, being close to a window may cause large data fluctuations. Therefore, weights can be assigned to the sensors based on their different locations and historical performance data, and then data weighted fusion can be performed. Generally speaking, data layer fusion does not cause data loss, and the results are the most accurate, but the amount of calculation is large and the requirements for system communication bandwidth are very high. In smart homes, sensors usually exchange data through wireless networks such as Wi-Fi and Bluetooth. Because network bandwidth is limited, the transmission of large amounts of raw data may cause network channel congestion, especially when data is frequently updated, which may affect system efficiency and response time. Because it integrates early on the data level, it is more suitable for applications that rely heavily on raw data, such as temperature and humidity control, lighting control, security monitoring, etc. Data layer fusion requires that sensors observe the same physical quantity. If multiple sensors do not observe the same physical quantity, the data can only be fused at the decision layer or feature layer.

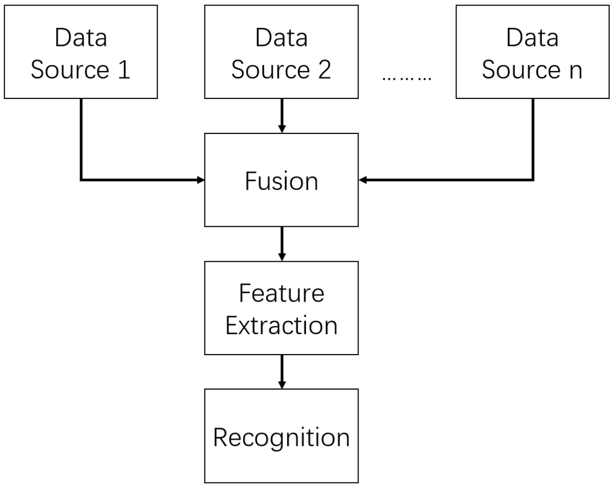

Fig. 1 Data layer fusion

3.2 Feature layer fusion

Feature layer fusion belongs to the middle level. The data feature is to extract features such as target contour, texture, time-frequency characteristics, and color distribution from the image or other processed data for classification and recognition[6]. What features to extract depends on the specific application (Fig 2). The system can extract key time domain features from sensor data, including average values, variability (standard deviation), extreme points (max and min), as well as skewness and kurtosis, through statistical evaluation. In the frequency domain, the system employs methods like the Short-Time Fourier Transform to break down signal frequencies over defined time intervals, the Wavelet Transform to conduct detailed analysis across different time and frequency scales, or the Hilbert-Huang Transform for examining complex, non-linear, and varying signals. These approaches are particularly useful for processing data from sound and vibration sensors. In feature layer fusion, PCA is a common feature extraction and dimensionality reduction algorithm that reduces high-dimensional feature data to a few principal components, thereby reducing redundant information, as shown in Table 1.

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Table 1 The PCA algorithm

Steps	
data matrix construction	$X = \begin{pmatrix} F_{11} & \cdots & F_{1m} \\ ? & \ddots & ? \\ F_{n1} & \cdots & F_{nm} \end{pmatrix}$
Centering	$X' = X - \mu$
Calculating covariance matrix	$\sum = \frac{1}{n-1} X^T X^T$
Eigenvalue decomposition	$Z = W^T X'$

PCA can transform feature data from various sensors into a lower-dimensional space, simplifying high-dimensional data into more compact and representative forms. PCA reduces the dimensionality of data while retaining the maximum amount of information. In smart homes, sensor data may be very large. PCA dimensionality reduction can significantly improve the system‘s real-time processing capabilities. For example, in a monitoring system, because the data stream generated by multiple cameras and sensors running simultaneously is very large, the system can process this data through PCA and extract key features to reduce data processing time and thus improve the system‘s real-time response capability.

Besides PCA, ICA is an algorithm for separating signals with statistical independence and is suitable for processing mixed signal sources. Unlike PCA, ICA assumes that the data source is non-Gaussian and tries to find a set of components that are statistically independent of each other, as shwon in Table 2.

Table 2 The ICA algorithm

Steps	
Centering	$X_{centered} = X - \mu$
Whitening	$Z = V^{-\frac{1}{2}} X_{centered}$
Maximizing Non-Gaussianity	$J(y) = H(y_{gauss}) - H(y)$
Signal Separation	$s = WX$

ICA can process mixed signals from multiple sensors in smart homes. For example, in environmental perception, the signals of multiple sensors may be mixed together and cause interference. ICA can effectively separate these signals and extract independent environmental features. Smart home systems typically incorporate a variety of sensors, including those for monitoring temperature, humidity, light levels, and motion, to ensure effective environmental surveillance. During operation, sensor data may be mixed or fail. The ICA system can separate the original signals of each independent sensor and detect abnormal data or failures of the sensor to ensure the stable operation of the environmental monitoring system.

Comparing PCA and ICA, the characteristic of PCA is to keep key information while reducing data dimensions, while the highlight of ICA is to extract statistically independent components. PCA is suitable for feature extraction and dimensionality reduction, and is adapted to data processing in simple scenarios, while ICA is stronger in processing mixed signals and separating independent components, and is suitable for tasks in complex, nonlinear environments. Both methods can play an important role in optimizing environmental perception and improving system performance in multi-sensor fusion of smart homes. In summary, the advantages of feature-level fusion are that it achieves considerable information compression, facilitates real-time processing. Since the extracted features are directly tied to decision analysis, the fusion results optimize the feature information needed for making decisions. Feature-level fusion typically employs either distributed or centralized fusion systems[10]. Feature-level fusion demands less computational power and communication bandwidth, though its accuracy may be compromised due to the loss of certain data during the process. In application scenarios such as smart homes, lost data details may affect the decision-making accuracy of the system. For example, in temperature and humidity control, if only features such as the mean and standard deviation are extracted while ignoring extreme values or instantaneous changes in the data, the system may not be sensitive enough to environmental changes, thus affecting the user experience.

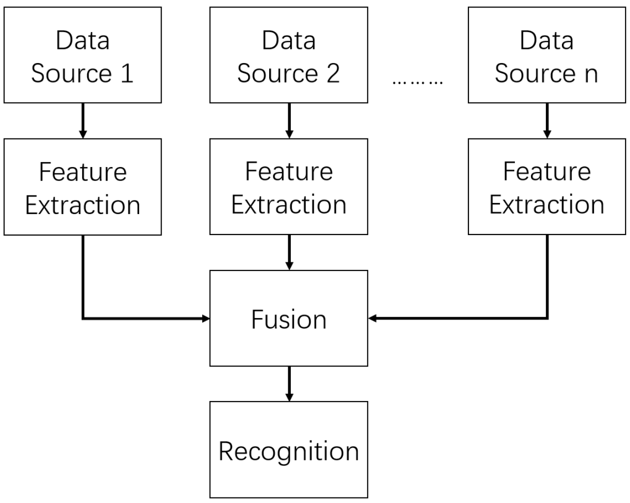

Fig. 2 Feature layer fusion

3.3 Decision layer fusion

Decision layer fusion is a high-level fusion, but due to the concentration of sensor data, the results produced by this method are relatively inaccurate, but its computational complexity and impact on communication bandwidth are the lowest. Decision layer fusion is different from the previous two. It does not directly process raw data or feature data, but fuses the independent decisions of each sensor (Fig.3). Since each sensor only sends its own decision result, the processing complexity and communication load of decision-layer fusion are minimal, making it highly appropriate for resource-constrained devices, such as edge systems or low-power sensors. Moreover, since each sensor makes its own decision, the decision-making layer fusion can process the decision results of different types of sensors. For example, the independent judgment results of motion sensors, smoke sensors, temperature sensors, etc. can be fused to obtain the final system judgment. This feature also makes it highly compatible and suitable for handling complex scene problems. In security monitoring systems, decision-making layer fusion is highly valuable in emergency alert systems, supported by advanced machine learning technologies. One of the most promising areas for designing integrated fire alarm and evacuation control systems is using artificial intelligence (AI) elements based on trained neural networks (NN) principles. AI is most suitable for classifying difficult situations using signs obtained from objectmonitoring data (smoldering, combustion, etc.) [11]. For example, AI can determine a set ofspecial characteristics or features of various fire situations using the collected data and apply them to decision-making in real fire situations[11]. Bayesian reasoning can be used for decision-level fusion, with independent decisions of multiple sensors used as evidence, and these evidences are fused through the Bayesian formula to update the final decision. Since the original data is further simplified and filtered, there is a disadvantage of insufficient accuracy behind the low computational and communication overhead.

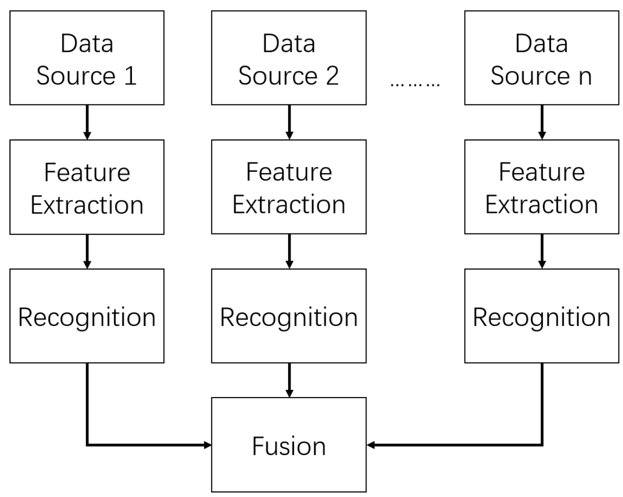

Fig. 3 Decision layer fusion

4 Limitations & Future outlooks

Table 3 summarizes the three calculation methods. It can be seen that any fusion method has technical or application limitations, which may prevent the system from achieving the expected effect in some cases. The paper will then discuss the main limitations of fusion methods as well as future improvements and developments.

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Table 3 Comparison of three fusion methods

	Data-layer fusion	Feature-layer fusion	Decision-layer fusion
Types of data processed	Sensor raw data	Extracted feature data	Independent decision results of each sensor
Applicable scenarios	Real-time monitoring and control, environmental perception	Behavior recognition, energy consumption management	Security monitoring, complex decision making, low power consumption devices
Advantage	High precision, complete information retention	Balance accuracy and computational complexity, suitable for heterogeneous sensors	Low computing and communication resource requirements, adaptable to complex environment
Disadvantage	The computation and communication overhead is high, and it is difficult to handle heterogeneous sensors	Information loss, feature selection is difficult	Low accuracy and unable to exploit potential correlations between sensor data

4.1 Limitations

4.1.1 Increased costs and complexity

In order to achieve the desired effect, multi-sensor fusion technology must deploy a large number of different types of sensors. The size and system complexity of smart homes will be very high. This is at the hardware level, so the complexity of system installation, operation and calibration will be further increased, which will hinder further large-scale deployment.

4.1.2 Difficulty handling higher-level cognitive tasks

Although multi-sensor fusion performs well in environmental perception, it still has many limitations for tasks that require high-level cognition and reasoning. For instance, a fusion system might struggle to interpret the complex behavior patterns of household members or foresee upcoming events based solely on basic sensor data.

4.2 Future look

4.2.1 Deep integration of artificial intelligence and multi-sensor fusion

Recently, advancements in artificial intelligence, particularly through neural network-based and algorithm-driven learning methods, have achieved significant progress in handling intricate datasets and identifying patterns. Looking ahead, neural network architectures such as convolutional and recurrent models may facilitate deeper analysis of complex data in multi-sensor fusion, thereby improving the system‘s intelligence. Through deep learning, the system can not only fuse data from different sensors, but also automatically extract complex features from the data to achieve more accurate environmental perception and behavior prediction. And with the help of artificial intelligence language models, their Application Programming Interface as the underlying layer, and a lot of training, in the future we can even have the kind of artificial intelligence butlers in the movies.

4.2.2 Improvement of sensor mapping

Residents‘ daily activities generate a wide range of sensor event streams, making the task of sensor mapping a crucial step for transferring activity features in smart homes. Despite its importance, many existing approaches tend to rely solely on sensor profile data or the ontological relationship between sensor placement and the furniture they are attached to for sensor mapping. In recent years, research in the field of sensor mapping has made significant progress, especially the application of deep learning and machine learning technologies, which has greatly improved the accuracy and adaptability of sensor mapping. These advances can improve the layout of multiple sensors in smart homes, meaning that sensor mapping and multi-sensor fusion can be combined. Dynamic mapping and adjustment can further improve the accuracy and speed of the system‘s environmental perception.

5 The conclusion

In conclusion, this study emphasizes the crucial role that integrating multiple sensors plays in improving the environmental perception capabilities of smart homes. This study demonstrates how different approaches contribute to a more thorough insight into the home setting by exploring various fusion methods, including those at the data, feature, and decision levels. The analysis shows that integrating multiple sensors enhances both the precision and dependability of smart home systems, while also optimizing decision-making and improving fault tolerance.

Innovative algorithms, like IPSO-ENN, further refine the efficiency and accuracy of data integration, achieving near-optimal results even with limited information about data reliability. This research provides valuable insights into the application of fusion technologies, offering a framework for future development in smart home systems. Future studies could focus on integrating advanced AI techniques to further enhance fusion algorithms and expand the-system‘s cognitive capabilities.

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