IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received December 17, 2019, accepted January 8, 2020, date of publication January 13, 2020, date of current version January 24, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2966400

A Systematic Review on Fusion Techniques and Approaches Used in Applications

SHAIDAH JUSOH[1] AND SUFYAN ALMAJALI[2], (Member, IEEE)
[1]Department of Computer Graphics and Animation, School of Computing Sciences, Princess Sumaya University for Technology, Amman 11941, Jordan
[2]Department of Computer Science, School of Computing Sciences, Princess Sumaya University for Technology, Amman 11941, Jordan

Corresponding author: Shaidah Jusoh (s.ibrahim@psut.edu.jo)

This work was supported by the Princess Sumaya University for Technology's Research Incentives Program.

ABSTRACT Fusion technologies have rapidly evolved. These technologies are normally customized according to the needs of domains. Despite a large number of publications on intelligence fusion applications for various domains, they are scattered. The aim of this review is to present the state of the art for intelligence fusion applications within a specific domain. We identified three major domains for the purpose, namely robotics, military, and healthcare, during the initial process of the systematic review. These three domains are always in need of superior intelligence. Articles were searched mainly in IEEE Xplore. We limit the range of publications to the year 2014 to 2019, to focus on the most recent publications. We adopt the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol to screen, filter and evaluate qualities of each retrieved article. As a result, we retrieved 675 articles at the initial stage of the search, we conducted screening and filtering process and reviewed 153 articles potential articles, and finally, we excluded 36 articles as they do not comply with our quality assessment criteria. Only 117 articles are included. The results of this study are a list of classified applications within the domains and a number of relevant techniques or approaches used in each classified application. The finding of this review showed that the most published works for the use of intelligence fusion are mainly applications in the robotics domain, where mostly used techniques are Kalman Filter and its variants. Outcomes of this study can be a guideline or an insight for researchers to further develop and implement in this field.

INDEX TERMS Intelligence fusion, data fusion, information fusion, multi-sensor.

I. INTRODUCTION

What is intelligence? It is a question that rises a great number of answers because an intelligence term is a dynamic concept. Intelligence is the key to humankind's survival. The success of any nation depends on the power of its intelligence, and the decisions made. The intelligence concept is the ability to make the right decision at the right time. To draw an intelligent decision, a collection of data or information is needed. Fusion is a fundamental process to combine or integrate various types of data and information, and a human normally performs this process using his/her brain automatically. Thus, the human mind remains the premier fusion processor. Researchers, scientists, and people in industries have been trying to imitate the human brain's capability to fuse data and information, to create intelligence technologies. Researchers proposed several techniques, approaches, and models to imitate how the human brain works.

Up to now, there is no single definition to define data fusion, information fusion, approach fusion, and model fusion. Authors in [1] reviewed previous definitions of data and information fusion, and they classified data and information fusion as a special case of synonyms. Nevertheless, data fusion or information fusion terms can be defined as the process of integrating [2], [3], associating [4], combining [5]–[8], a collection data or information from single or multiple sources.

Through our survey on published works, we discovered that integration and combination terms are most commonly used in referring to fusion. Many works of literature also reported on sensor fusion. It is a process of combining any type of data and information from a sensor or multiple sensors. Researchers have been applying and implementing fusion techniques in many types of domains to create intelligent applications that can make intelligent decisions without

The associate editor coordinating the review of this manuscript and approving it for publication was Yassine Maleh.

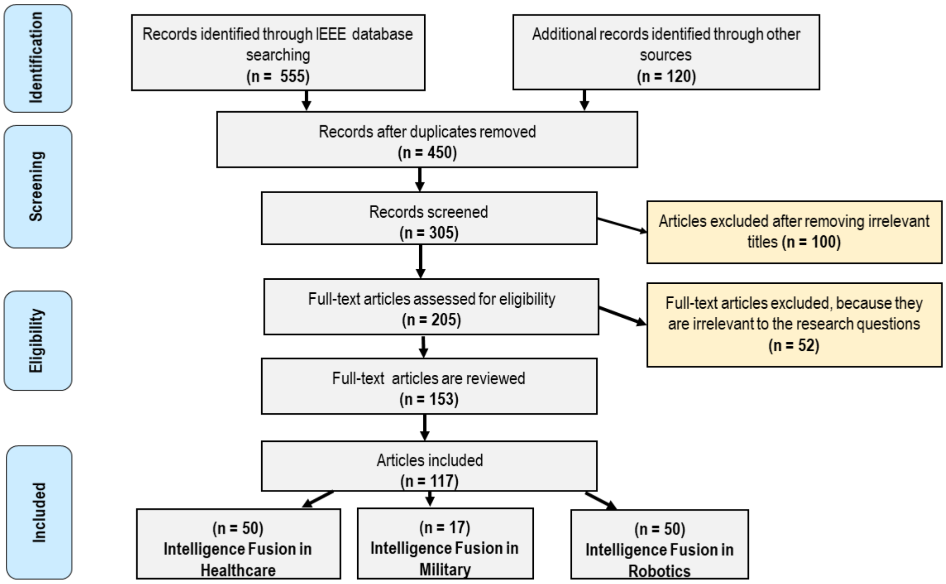

FIGURE 1. A PRISMA flow of this systematic review.

human intervention. However, to the best of our knowledge, there is no single paper that presents the use of intelligence fusion in applications within identified domains. The discussion of intelligence fusion applications is scattered.

This systematic review aims at identifying and classifying types of applications that make used of fusion techniques and approaches within major domains. After browsing and reading published works of literature on this topic, we limited the review into three domains: military, robotics, and healthcare. We noticed that these three domains are the most in need of superior intelligence, and worth to study. This paper is organized as follows, section II presents the procedure and process that we follow in conducting this review. Section III presents identified applications for a military domain, followed by robotics in section IV, and healthcare domains in section V. Section VI presents the summary of this review and we address our contribution in the conclusion section.

II. METHODOLOGY

In conducting this systematic review, we have adopted the PRISMA approach [9]. Figure 1 shows an overall summary of the process of article selection including the inclusion and exclusion at each step according to the approach. The approach is conducted within six phases as follows.

A. RESEARCH QUESTIONS

The first phase is to formulate the main research question (RQ1) as guidance and direction in this study. Then we define the second research question (RQ2) to get into details of the research topic. In the third research question (RQ3), we dived into the technical aspects of the topic. The three research questions are as the following:

- RQ1: What are the main domains that make use of intelligence fusion?.
- RQ2: What are applications of intelligence fusion in an identified domain?
- RQ3: What are techniques or approaches used within in a classified application?

B. DATA SOURCES

The search process started with the identification of data sources. We conducted initial browsing in four major repositories namely, Google scholar, ACM digital library, IEEE Explore, Elsevier, and Springer. During the initial browsing, we noticed concrete works of the intelligence fusion are stored mainly in the IEEE Explore compared to other repositories. This is attributed to the nature of this study, more towards Engineering and Computer Sciences. Thus IEEE Explore is the main data source for this study. During the initial browsing, searching, and retrieving articles we managed to answer RQ1 when we discovered that a great number of intelligence fusion works were reported in military, robotics, and healthcare domains.

C. SEARCH PROCESS

To focus on the most recent works for the identified domains, we extracted the literature from the year 2014 to 2019. The search was also limited to journals and conferences. The first step in the search process is to formulate efficient search keywords. The search keywords we used in this study are:

- intelligence fusion in military.
- information fusion in military.
- data fusion in military.
- intelligence fusion in healthcare.
- fusion in medicine.
- intelligence fusion in robotics.
- fusion sensors in robotics.
- information fusion in robotics.

The search found 675 articles, which 555 of the articles were retrieved from IEEE Explore. Duplicates were found. This was due to multiple keywords retrieved the same articles in searching, or they were stored in multiple repositories.

D. SCREENING PROCESS

We eliminated the duplicates, then we conducted the first step of the screening process on 450 articles. This screening process includes checking its relevancy to the identified domains. This process had resulted in the removal of 145 articles, and we continued the screening process for another 305 articles. In the second step of the screening process, we reviewed the titles and abstracts of the articles. Articles in which their titles are not relevant and the presentation of their abstracts are poorly organized were removed. This process had eliminated 100 articles. The assessment was conducted on the remaining 205 articles, to determine whether these articles worth to be reviewed by browsing their whole contents. In this assessment, we focused on one criterion; is the article related to RQ1 and RQ2?. This process had resulted in the removal of another 52 articles.

E. REVIEWING PROCESS

The screening process had left 153 articles to be thoroughly read and reviewed. In reviewing the final stack of articles we had used the following criteria for inclusion and exclusion.

- C1: Is the article adds a significant technical contribution?
- C2: Is the article is well-organized?
- C3: Is the article presents clear techniques and approaches?.
- C4: Is the article justified the techniques or approaches used?

For each criterion, we gave a score of 0 (no), 0.5 (partial), and 1 (yes). We used three types of facts to guide us in determining the score value for each criterion; 1) the article was published in a well-known journal/conference, 2) the ''reads'' number for the article, and 3) the article has been cited by other works. The summation of the scores defines the quality of each article. We set the threshold score to be 2.5 [10]. Any article that scored less than 2.5 was excluded. This process had excluded 36 articles, resulted in 117 articles to be included in this study.

F. FINDINGS DOCUMENTATION

The findings of this study are presented in the following sections. We classified applications for the studied domains, and present each application separately (RQ2), and we present an answer for RQ3 in the summary section.

III. MILITARY

The missions conducted by military and law enforcement agencies are considered complicated due to several reasons. First, it is sensitive by nature, as it involves people's lives and has a major impact on countries and cities. In addition, it usually requires the cooperation of several entities in real-time. Also, it involves several persons assigned to work on a certain mission. Besides, the military missions involve receiving data from the different sources, in different formats, and requires combining the knowledge into one. In this section, we discuss several military applications that utilized the concept of intelligence fusion.

A. 3D OBJECT DETECTION

An autonomous vehicle (AV) uses sensory data and converts it into semantic information that allows autonomous driving. Most of the AV techniques have employed 2D object detection as a basic feature for the perception. 2D object detection is limited as it does not have the depth and the multi-dimension that will be offered when dealing with a third dimension. 3D object detection allows taking advantage of size information, volume, and the path which facilitates the AV process.

Sensor fusion has been researched heavily in the past. Most research projects focused on fusing the intelligence from multiple sensors at the object level not the raw level such as LiDAR, RADAR, FLIR [11]–[13]. The high level approach in general includes taking one sensor at a time, like Camera, perform the analysis on it, produce output results that could be identification of the presence of objects such as human or cars. The fusion part comes as a next step by combining the produced results of objects from multiple sensors to form the overall picture about the scene or the situation.

Authors in [14] focused on improving the detection of 3D objects using neural network architectures. The used data sets of images from sensors taken by autonomous driver. Autonomous driving is considered the future of driving as major leading companies such as Google started developing their own solutions that are under the testing stage now. In military, autonomous driving constitutes an a major solution to many threats that can face the soldiers in the field. On one hand, it helps driving vehicles without the need of human being inside. Also, it can help automatically detect situations that are not easily detectable by military personals which helps create more efficient and successful operations.

As showing in Figure 2, the authors in [14] proposed a solution that fuses that LiDAR data with the camera data efficiently. Their approach is based on supplementing each 3D raw data with features acquired from the RGP image after processing these features via a 2D Object Detection CNN filter.

In [15], in a similar fashion to [14], authors exploited both LiDAR and cameras. They proposed a solution for multi-sensor data fusion for 3D object detection by using layers for continuous fusion. The layers fuse the features received from two input sources: The camera image stream and the BEV LiDAR stream. The fused data results into the BEV features maps. The camera image data is fed as input at multiple resolutions levels, from high resolution to low resolution as

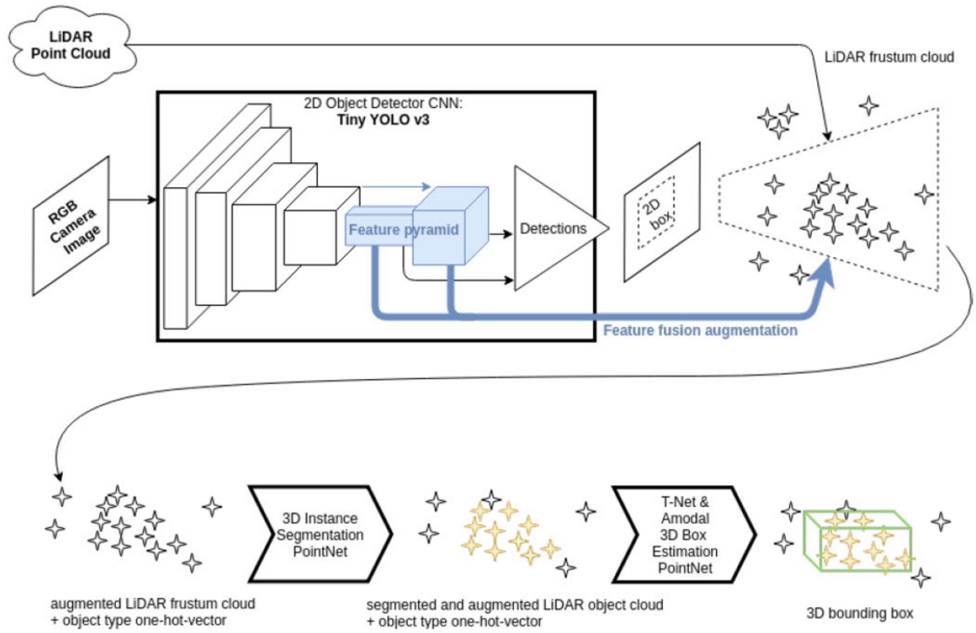

FIGURE 2. LIDAR-Camera fusion approach source [14].

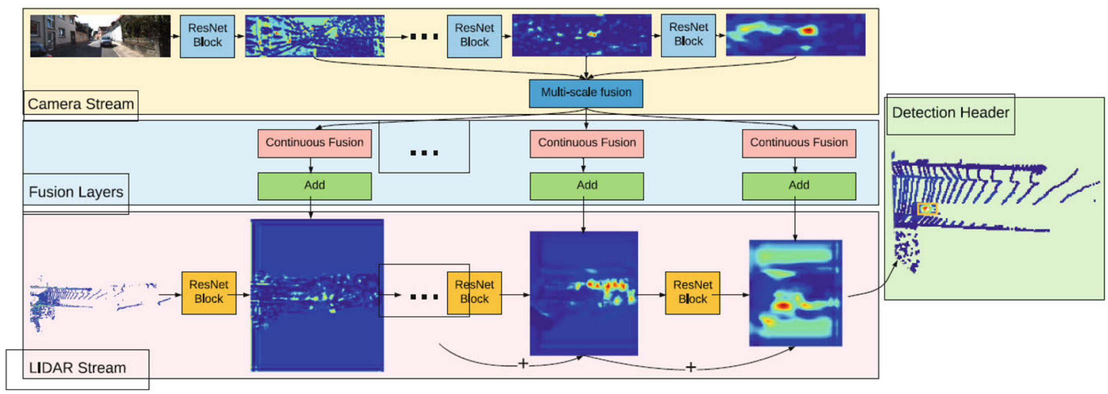

FIGURE 3. Proposed solution architecture [15].

each level will provide different features. Figure 3 shows the proposed model.

B. DATA FUSION IN WIRELESS SENSOR NETWORKS

Wireless Sensor Network (WSN) is utilized deeply by armies and law enforcement agencies. WSNs allow a group of nodes to form a network in any place without requiring any existing infrastructure. In general, WSNs contains large number of scattered nodes/sensors in the field that sense temperatures, humidity, etc. WSNs are considered a major type in Internet of Things (IoT). WSNs forms dynamically clusters and elect cluster heads to lead each cluster. And cluster heads accumulate and repot the data back to some base station. Due to the sensitive nature of the WSN applications, it's success is measured by the quality of data it provides in addition to its power efficiency. WSNs use data fusion from all these sensors and cluster headers to provide unique data to the users. The created data represents new high-level information that cannot be obtained by looking at one sensor data or few sensors data. In addition, data fusion helps reducing energy consumption [16]. Researchers have developed several data fusion approaches. The three main categorizes of data fusion techniques in WSN includes include probability theory [6], fuzzy algorithms [17], and a combination of fuzzy and neural networks [18].

Authors in [17] proposed a solution for fusing data efficiently and accurately. The solution relies on a fuzzy-based data fusion algorithm as shown in Figure 4. The solution main idea is to reduce the number of transmission of data being delivered to the base station by using fuzzy rules that detect correct values. This ends up in reducing energy consumption and more accurate decisions at the base station.

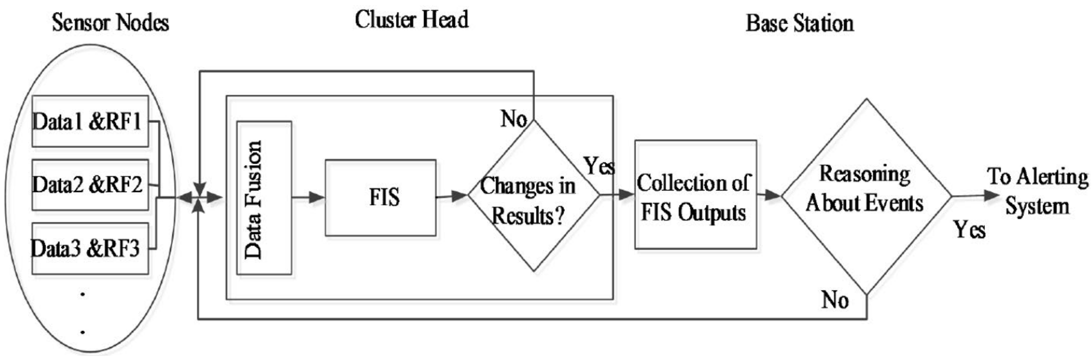

FIGURE 4. Proposed data fusion approach for WSNs [17] .

C. MILITARY IMAGE CAPTIONING

In complicated defense missions, military and law enforcement agencies rely on input coming from several types of activities such intelligence, surveillance, and reconnaissance. Sensors provide data in large quantities and in different formats such as audio, images, video, and text. This yields to a big-data problem that fusing it requires complicated logic. One of the main military applications in this regard is image captioning which allows captioning the image automatically with text based on data gathered from different sources. Automatic captioning helps when dealing with large number of images being generated at a quick pace and constantly.

Authors in [19] developed a deep learning approach for image captioning in military. Convolutional Neural Network (CNN) were used to achieve data fusion. Other researches used language models for image captioning [20].

D. FUSING INFRARED AND VISIBLE IMAGES

Several surveillance applications requires capturing images from different sources and analyzing them. Images could be of different types such as visible images and infrared images. Visible images represent what a user can see when normal human eyes. At night, a user would not be able to see anything.

Infrared images show the differences in temperature. Different objects have different temperatures. An infrared image allows objects to be tracked at night or semi-dark cases. Even in the daytime, infrared images can show information that is not seen by the visible images based on the colors of the object's background. Fusing infrared along with traditional visible images produce rich results for the analysis. One main challenge is the difference in resolution and image quality between infrared and visible as different quality image sources can be used in the same scene. High quality infrared images requires high cost cameras which is one reason for the quality difference. Figure 5 shows an example on image fusing.

Fusing infrared with visible images can be accomplished at several levels [21], 1. Pixel level (low level), 2. Feature level (intermediate level) and 3. Symbol level (high level). The lower level fusion has access to all of the details of the raw image which allows not to miss any data while fusing. At the same time, lower-level suffers the efficiency issue as it is required to deal with large number of bytes. On the Symbol level fusion is at the high level which does not allow access to raw data and results in missing important data in certain cases.

Authors in [22] proposed a new algorithm for fusing infrared with visible images to produce higher quality images. Their algorithm, Different Resolution Total Variation (DRTV), dealt with the fusion problem as convex optimization problem, minimization problem.

E. OBJECT DETECTION

Object detection has several applications in the military field. This includes detecting of moving objects of all types such as human, vehicles, airplanes, animals, drones, and other types of objects. In [23], they used hyperspectral imagery (HSI) which is produced by remote sensing. They extracted multiple information types from the HSI imagery using several statistical methods. Extracted information includes superpixels by applying principle component analysis (PCA) and k-means clustering. Also, the correlation between each superpixel and the object spectral is calculated using self-similarity methods.

In [24], the used imagery information extracted from UAV systems along with deep learning techniques to detect the presence of heavy construction vehicles/equipment such as excavators and bulldozers that is near the military communication network lines.

F. TARGET TRACKING

In addition to detecting the presence of objects, tracking certain objects and targets is heavily employed in the Military. In [25], they integrated three techniques, Deep Learning, Kalman filter, and a correlator to track Aerial targets from imagery information.

Radio Frequency (RF) Emitter tracking is essential in the military for tracking the movements of suspicious targets. This includes tracking traditional RF bands such as 800MHz and 900 MHz, in addition to tracking cell phone users.

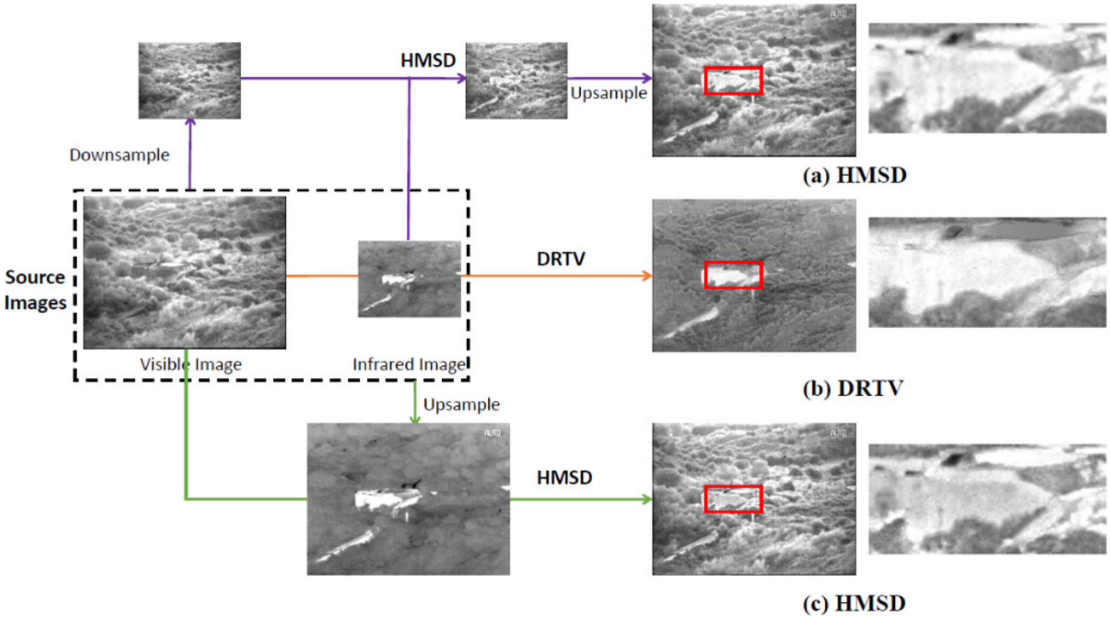

FIGURE 5. Example of image fusing.

Tracking technologies include combining one or more of the several information that comes from geolocation using cell towers, GPS-based positioning, RFID-based locating techniques, Zigbee-based, and WiFi-Based.

In [26] authors used data fusion of infrared signals along with camera data to perform indoor positioning of targets. In [27], authors proposed a solution for Geolocating Multiple Emitters using electronic support measures sensors.

IV. ROBOTICS

Robots have been seen as an alternative for addressing labor shortages. The use of robots may increase and improve the quality of products as well as decrease production costs. Nowadays, robots are widely used as workers in manufacturing sectors to replace human workers [28], [29]. Examples of manufacturing robots' tasks include packaging, locating, assembling, and so on [30]. In this context of the environment, the robots have to make plans and decisions, and execute them in the form of its behaviors [31], as one integrated system. Intelligent robots with independent capability, so-called service robots, have been extended to work (perform tasks) in non-manufacturing environments, such as homes, hospitals, offices, and so on, to provide services to humans [32]–[34]. A robot is a machine, and robot control systems are controllers. The controls systems are designed in such a way that operational speed, functions, are compatible with the needs of the robot's tasks [35].

Robots are one of the artificial intelligence applications which have the capability of choosing a path, positioning autonomously, navigating its environments, avoiding obstacles, detecting an object, localizing itself, detecting errors, and activating recovery plans. Robots come in various shapes, such as a human-like, with two legs, or an animal with more than two legs, or like vehicles with wheels. The shapes depend on their functions and purposes.

A. LOCALIZATION

Robot localization is a process of discovering a robot's location within its environment [36], [37]. It is a fundamental issue for any kind of mobile robots. Normally, a robot observes its motion and environment through onboard sensors [38]. Techniques for robot localization deal with the estimation of the robot location and noisy observations [38].

Sensor fusion techniques such as extended Kalman Filtering(KF) [39], [40] and it variants [41] had been used in robotics for an object estimation [42], a robot pose estimation, localization [43], [44] and navigation [45]. Kalman filter (KF) is normally used in real time applications to fuse dynamic sensor information [46]. According to [38], KF and EKF are the most common techniques for robot localization, however, because KF or EKF are fusion methods which embrace iterative algorithms to handle non-linear and linear models, the convergence is always uncertain [47]. The desired state representation is based on the sensor input which is known and fixed upfront.

Authors in [41], however, made an effort to fuse unknown information generated by multiple sensors using a deep learning approach. While the work of [47] determined an accurate position of an autonomous mobile robot by fusing data from inertial sensors, inertial measurement unit (IMU), and vision data from a camera.

Advanced perception ability is also important for a robot to interact physically with its world, such as grasping an object as shown in Fig 6. Authors in [48] introduced contact

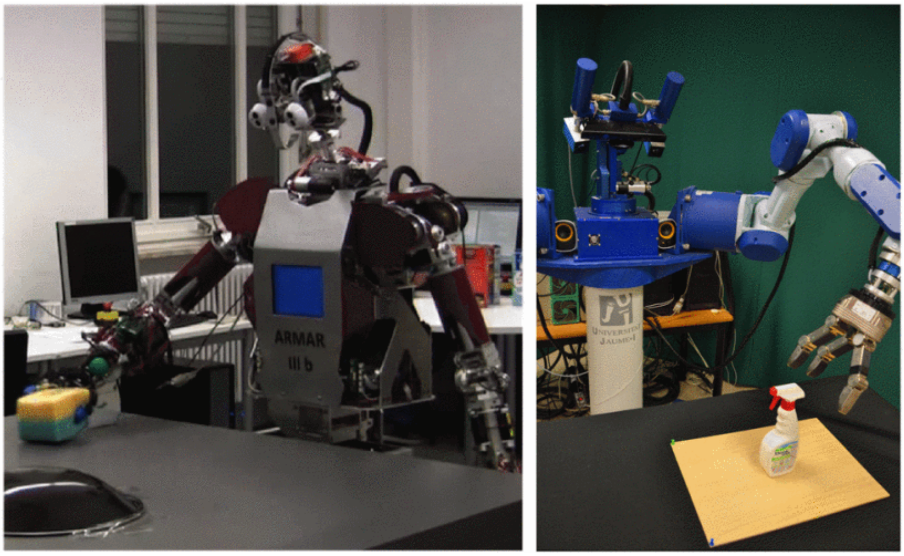

FIGURE 6. Contact detection and localization [48].

detection and localization from different sensory modalities using a sensory information fusion approach. These modalities include tactile, force-torque, laser, vision, sonar, accelerometers, and so on.

Precise localization [49]–[51] system is important for an autonomous robot, especially an autonomous driving vehicle. The outdoor localization technique uses a global positioning system(GPS). However, the GPS decreases a cumulative error of odometry data from unwanted effects of slippage. When GPS outages are considered, the positioning inaccuracy is not a piece of reference information, to get an exact indoor localization. Authors in [49] proposed a data fusion technique for more precise indoor localization where they extended a sensor fusion system to integrate data from both sources; magnetic sensor and odometry, where they applied the Ackerman steering geometry to develop the odometry model. The odometry data was collected from encoder information located at the rear wheels and steering.

Further, authors in [50] determined the localization of mobile robots in a complex environment by combining stereo vision localization with inertial measurement. They proposed a fusion technique that uses dual Kalman filter (DKF). In this approach, the localization system depends on active sensors, like ultrasonic and laser equipment. The work of [52] also proposed for localizing underwater robots through a sensor fusion.

B. SELF-POSITIONING

Self-positioning is a sub-topic of localization. Localization is a robot's ability to locate itself in its map-environment while self-positioning is a robot's ability to adjust its position and orientation with respect to the map. Researchers and engineers developed various systems, sensors, approaches, and techniques for robot positioning [37], [53].

For example, authors in [53] developed a self-positioning method for indoor navigation to achieve better positioning accuracy. The method integrated information from multi-sources such as an inertial navigation system, ultra-wideband, and a 3D laser scanner. A map is also commonly used to describe a robot's environment. The map contains additional elements of information like static obstacles and landmarks. Authors in [54] proposed an information fusion method to observe and collect information from several sensors and optimize them using certain criteria then represents a collective of information as a grid map. The method enhanced the accuracy of a robot's position, and the mapping results confirmed the reality.

Underwater robots' tasks include explorations, inspections, and constructions. Thus, the underwater robots should have the ability to make accurate pose estimation to complete the mentioned tasks by using collected information from sensors. Authors [55] fused pieces of information from inertial sensors and optical images, to have a consistent pose of an underwater robot.

Self-positioning is very necessary for industrial robots to perform assembly tasks. Authors in [56] presented a multi-modal information fusion approach for the development of an intelligent perception system that can recognize actions and generate tasks in an industrial assembly environment. The multi-modal information fusion uses prior knowledge of assembly tasks to obtain real performance.

Furthermore, robots should identify their activities instantly to complete the assigned tasks. These robots are usually equipped with sensors. However, sensors such as gyroscope, servomotor, and accelerometer have significant data differences. Moreover, an individual sensor is not able to perceive the whole environment completely or performed weakly. The solution is to use multi-sensor fusion as [57] reported on using multi-sensor fusion to fuse information from multiple sensory streams for robot-self activity recognition

C. NAVIGATION AND OBSTACLE AVOIDANCE

Navigation is a process of guiding a mobile robot or an autonomous robot to travel through its environment. The problems of navigation rely on ''where'' and ''how'' questions, '' where the robot is ?'', where it is going?'', and ''how it is going to get there?'' [58]. Data from various sensors surroundings of the vehicle or robot such as cameras, laser scanners, ultrasound sensors, GPS and magnetic compass are gathered, processed, and selectively fused for a reliable decision [59]. The decision is deployed in navigation and control.

Human supervision in robotics normally occurs at the highest level and the robot uses machine intelligence to complete tasks by analyzing the feedback that came from sonars, a camera, and bumper sensors. For example, the bumper sensor gives feedback on collision detection and sonars act on distance monitoring. Authors in [60] reported on enhancing brain-robot interaction by fusing machine intelligence and human. The fusion has alleviated the brain load and increase the efficiency of robot execution.

Manual-automatic fusion control is another effective way for the robot (especially a hot line work (HLW) type of robots) to deal with unexpected scenarios during its execution. Authors in [61] presented a control method to generate a fusion control strategy for HLW robot. The method was based on event-based planning. The control strategy helped HLW robot to avoid unexpected obstacles and keep its trajectory as preplanned.

In the context of mobile robots, their working environments are normally unstructured and contain undetermined characteristics. These robots are required to perceive externally changing the environment for difficulty-obstacle avoidance and autonomous navigation. Information fusion from multi-sensor is essential for the robots' obstacle avoidance. Authors of [62] studied common fusion algorithms for multi-sensor information and claimed fuzzy logic control (FLC) and fuzzy neural network (FNN) perform better in a nonlinear system. The fusion approach which is obtained from a combination of FLC and FNN is feasible and effective in obstacle avoidance and path planning for mobile robots. Others like authors in [63] proposed a navigation approach that contains three components, 1) target search, 2)obstacle boundary and 3) a supervisor's behavior in an unknown environment. The behavior was obtained from a fusion of swarm based algorithms Reference [64] reported on a feature fusion approach, where features from both sensors, sonar, and laser are fused to overcome the shortcomings of a single laser or single sonar for the obstacle avoidance. Reference [35] presented a fusion technique which combines two modules of obstacle avoidance; ultrasonic and infrared. The ultrasonic is a single point of obstacle avoidance while infrared is based on double-crossing obstacle avoidance.

D. FACE AND HAND RECOGNITION

Face recognition is essential in a human-robot interaction when it comes to the interaction between a service mobile robot with a human. Both are normally existing within a specific range of space in the same environment. Despite face recognition has improved, it is still difficult for a multi-pose and multi-recognition. Researchers such as [65] fused wavelet images for a single sample face recognition method. The method was able to detect and recognize the different size of human faces with their perspective of angles and ornaments.

Furthermore, facial expression recognition is also important in the development of these intelligent robots. The emotional interaction between a human and a robot can be observed through facial expressions. A combination of the human voice and visual information is used in [3] for the fast identity registration system for face detection. Videos, a sequence of images, and static images were fused to determine human emotions. With the facial expression recognizer, the robots can emotionally communicate with children and assist the elderly. Authors in [66] reported the feature fusion technique for facial expression recognition. The feature fusion was conducted on the extracted features from salient areas of the face, as shown in Figure 7.

Besides the face and facial expression recognition, hand sign recognition in a real-time is also crucial in human robot interaction (HRI). As reported in [67], hand sign recognition resources are limited compared to face recognition. The major challenge of real-time hand recognition is complicated and cluttered backgrounds, which can distract the recognizer. The authors in [67] proposed a multimodal information fusion for HRI. In their work, they combine two types of modal, hand recognition and emotion recognition. The recognizers aimed at complementing any discrimination. They also reported on combining a feature vectors based approach with a model feature-based approach for face recognition. Information such as position feature points and appearance texture of the face is used to determine the facial expression.

E. GESTURE OR GAZE CONTROL

Several techniques have been used in gesture and gaze control in remote robotic operation as reported in [68]–[71]. Gesture control is a robot control system which allows gestures to control mobile robots. Reference [72] introduced a multi-mode information fusion classifier for a gesture control. The classifier combines information from two sensors, an inertial sensor, and an electromyography sensor. The classifier was reported to be portable, robust, and intuitive

By using deep learning approach, authors in [68] used deep learning approach to fuse audio and visual data to control robot motions and to control the head of the robot to point to a human user.

F. OBJECT TRACKING

Object tracking is one of the data fusion application in robotics. Authors in [73] presented a tracker system that

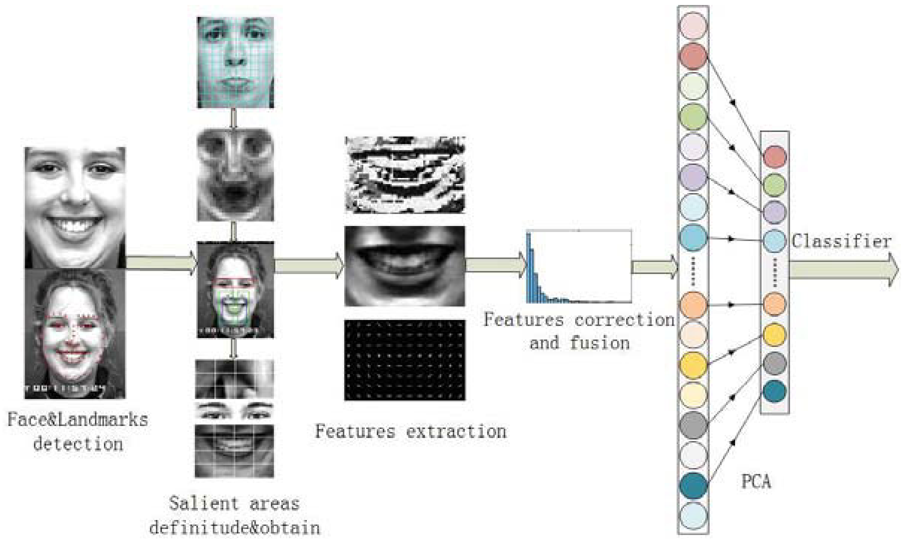

FIGURE 7. Feature fusion facial areas [66].

is based on a data fusion technique. The fusion technique fused radial and 2D data, the first data was observed from a radar sensor, while the latter from a CCD camera. Authors in [74] reported a formation control in a multi-robot system, to determine the position of a robot that behaves like a leader. The formation control was obtained by fusing information from the laser sensor and a camera.

Robotic perception is also a key technology for autonomous vehicles and advanced driver-assistance systems. The safety and efficiency of an autonomous vehicle depend on the ability of the autonomous vehicle to perceive its surrounding environment. One of the challenging problems in the perception task is to track dynamic objects such as a moving car, or a bicycle, or a walking pedestrian. The autonomous vehicles have to be able to predict the future trajectories of these objects.

Authors in [75] tried to tackle an extended object tracking problem, where they proposed a technique for fusing negative and positive information, and an algorithm to estimate state the extended object. The technique was performed in two steps; the first one is deriving state vectors of an extended object, and the second step is extracting negative geometry information that appears between the extended object and the vehicle's sensor.

Service robots such as a walking assistant robot are seen as a solution to elderly people in walking. However, elderly people can easily fall. Fall prediction is necessary. Authors in [76] used a data fusion technique to implement a fusion center that fused extracted features from tactile-slip sensor, gyroscope, and acceleration sensor (as shown in Figure 8) to make fall prediction.

G. LOCOMOTION TASKS

Authors of [77] defined locomotion as "the process of moving from one place to another". It is a motor action, which executes the whole "body" of a robot or a part of it. Locomotion tasks are evaluated in the robot's capabilities in walking up a ramp, moving through irregular steps, or overcoming a gap. Locomotion tasks [78]–[80] remain a challenge to mobile robots whether they are indoors or outdoors robots, especially when motion control is complex and dynamic. Locomotion becomes a crucial capability for robots that are deployed in a medical endoscope, industrial surveillance, a search and rescue domain [79].

Authors in [80] proposed to accelerate locomotion tasks; they explored variance reduction and asynchronous approaches to introduce a distributed fusion. Authors in [78] introduced an adaptive fusion technique. The technique combines features from the accelerometer and paw sensors, to make the recognition more robust. Naive Bayes classifier was deployed in this technique. It was reported that the efficiency of locomotion tasks increased.

V. HEALTHCARE

Healthcare sector continues to grow, and like other sectors, and it is expected to provide essential services and cares for a human being. Medical practitioners and public people started to expect more and more for the use of intelligent systems and services in their daily life. The use of intelligence fusion applications in healthcare will support phenomenal systems and services. We identified five major applications that are currently make use of intelligence fusion. These applications include monitoring systems and wearable technologies, wireless body sensor networks, medical diagnosis, and capsule robot.

A. MONITORING AND WEARABLE TECHNOLOGY

Monitoring systems is one of the necessary applications in healthcare to improve chronic diseases management. Usually monitoring systems are used to monitor elderly and disabled

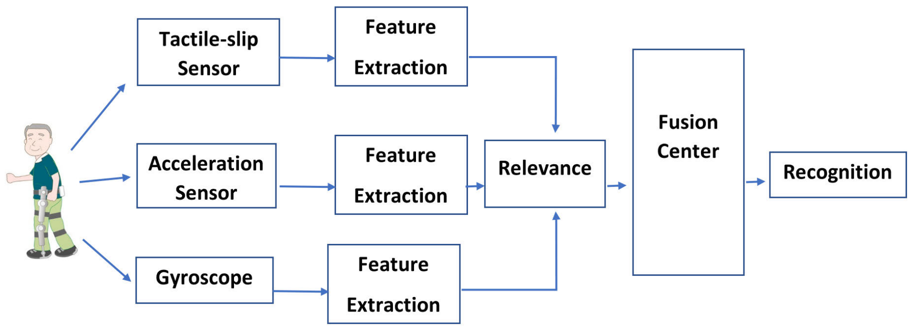

FIGURE 8. Data fusion for fall prediction [76].

patients. It is a surveillance solution to observe any vital signs to control patients' health condition efficiently. By using monitoring systems, hospitalization can be avoided [81].

According to [82] and [83], the healthcare sector has used three major kinds of monitoring practices. These include wearable, practice-vision-based, and environmental. Wearable monitoring technique is based on wearable technology. This technology [84] is getting popular in healthcare products or applications and is used to monitor user's health. It is a device that a patient can wear on his/her body, and can be taken off at any time, or it is embedded in the body. According to the report published in eMarketers [85], almost forty millions of adults in the United States have been using wearables such as fitness trackers and smartwatches. Wearables also have gained much attention from the healthcare systems, medical practitioners and public because it enables the observation of relevant signs associated with physical performance or active without interrupting the daily living activities of the patients [86]. These devices are used to monitor a patient's motion associated with physical activities and widely used in fitness tracking, fall detection, rehabilitation, and others [87], [88]. The main key of any wearable technology is sensors that quantify biological parameters (data) from the human body. Examples of non-invasive sensors that are used to monitor health signal are patches, wearable devices, and smart garment [89]. According to [90] wearable devices that comprise of inertial sensors [91] are the most profitable ones. Nevertheless, the development of wearable devices is seen as an opportunity to utilize health applications for monitoring patients' physical activities such as walking, running, sleeping [89].

Authors in [89] reported that wearable sensors had been used to collect clinical measurements such as blood pressure and blood glucose. Various sensors such as gyroscope, a proximity sensor, and accelerometer are currently available on smartphones to be used to detect human mobility and activity [89]. Research work on fusion has been conducted for wearable technology. For example, authors in [92] presented a fusion system that combines images from a camera and inertial signals from a wearable inertial sensor concurrently, to detect and recognize a patient's actions in-home healthcare. Their experiments focus on the patient's movements including lying down, sitting, standing, and falling down, and other actions of interest motions such as from standing to sitting, sitting to standing, standing to lying and so on. Authors in [93] proposed a hierarchical fusion algorithm to recognize human activities such as walking, running, climbing and rope skipping.

Authors [94] reported on wrist-wearable devices which contain sensors to collect raw data of invasive measurement for further intelligent analysis. Reference [95] introduced a non-invasive wearable such as smart belts, smart socks,smart wrist-bands, and user-friendly sensor to analyze signals from a walking pattern to determine health-related information. Authors in [82] reported on effective data fusion techniques from impulse-radar sensors and depth sensors for monitoring the elderly. The fusion technique had improved the accuracy of position estimation. Authors in [86] proposed a data fusion technique to merge data collected from wearable and environment simultaneously to recognize physical activities such as the walking activities. Their approach is based on a transfer learning approach. Reference [96] presented a breath monitoring system (e-Breath) using a wearable microphone which is connected to a smartphone. The work [96] proposed an effective feature fusion model for breath detection. They conducted experiments on 5,700 breath events, and the obtained results indicate that the fusion model performance overcomes the single model. e-Breath can be utilized for diagnosing and treating respiratory diseases.

B. WIRELESS BODY SENSOR NETWORKS

Wireless body sensor networks (WBSNs) is a kind of monitoring systems. It is a technology that allows continuous remote monitoring. Remote monitoring is becoming popular among both patients and healthcare professionals, who want their health to be monitored outside clinical settings such as at home. The technology has been used widely to aid patients who are suffering from heart conditions, diabetes, and other chronic diseases [97]. WBSNs collect and analyze critical signs data by using different types of biomedical sensors [98]–[101]. These signs include stress level [102], ECG [103], body temperature [104], heartbeat [101], blood pressure, EEG, and so on. However, WBSN has its challenges such as energy resources are limited and a large amount of heterogeneous data for early detection decisions of emergencies. Researchers have seen fusion as one of the possible solutions for tackling the challenges. Authors in [105] proposed a multi-sensor data fusion approach that uses health signs scores to determine the risk level of a patient. The approach was developed using the fuzzy system and a score determination technique, where the vital signs are assigned with the past and current values. The approach was evaluated using real healthcare dataset, each time an emergency is detected, a corresponding decision is made.

Furthermore authors in [106] proposed on using multimodal health data fusion for a remote healthcare framework. The multimodal data fusion is an integration of the health data collected from WBSN, cloud big data fusion, remote collaborative diagnosis system, and a treatment service expert decision support system.

Authors in [81] presented a data fusion model which combines information from various biosensors to decide about the patient's situation. Fuzzy set theory was used to develop the data fusion model. The model aggregates the received raw data during a consecutive period using fuzzification procedures, and then the fusion model selects a decision that has the closest feature values to the aggregated dataset while authors in [81] reported on the use of data fusion model which is based on fuzzy set theory and decision matrix for a biosensor data management.

C. MEDICAL DIAGNOSIS

Researches have paid attention to utilize fusion models, approaches, and techniques in medical diagnosis. Authors in [107] presented the deployment of a learning-based method for a fusion approach. In the work of [107] 3D preoperative high-quality anatomical information was fused with live 2D intraoperative imaging using noncontrasted 3D C-arm CT.

Information fusion has been also very demanding in medical pattern recognition applications [108]. According to [109] information fusion in pattern recognition are categorized into feature fusion [96], [110]–[116], model fusion [81], [98] and decision fusion. Feature fusion is seen to be the most effective way to improve the performance of decision models. Authors in [108] proposed a feature fusion algorithm to classify electroencephalogram (EEG) signals based on discriminant correlation analysis. They recorded EEG signals from the brain and generated features matrices from signals and decomposed wavelet to derive a set of sub-multi-view features. Then optimization was applied to extract statistical features. The fusion technique concatenates the features to derive low order discriminant features.

Alzheimer's disease (AD) has been known as one of the chronic diseases. Early diagnosis for AD is essential, such that any early deterioration can be intervened. Authors in [116] had made an effort to propose an AD recognition method using data fusion of T1 and DTI images. In the context of diagnosing illness, authors in [117] presented

FIGURE 9. Examples of capsule endoscope.

information-fusion algorithm to make an intelligent decision about a patient illness. The method deploys the Dempster-Shafer theory. Reference [117] also reported on merging information obtained from the web, local medical knowledge database, and a user electronic health records, upon receiving a description of patient's symptoms.

D. MEDICAL IMAGING

Fusion in medical imaging is a process of combining multiple images from single or multiple sources, to improve quality and reduce redundancy and randomness of medical images. These images are used in diagnosing and assessing medical problems [118]. Medical image fusion techniques help physicians to combine several diagnoses, conduct operative planning and guidance, and suggest treatments [119].

Authors in [115] reported on a feature fusion approach for evaluating the placental maturity. In this work, information fusion was applied on the extracted blood blow information from the color Doppler energy (CDE) images and the gray-scale intensity ultrasound images. The feature encoding was then applied on the fused information to determine placental maturity stage.

E. CAPSULE ENDOSCOPE

A capsule endoscope is also called a capsule robot as shown in Figure 9 is one of the robotic technologies which had been widely used in healthcare. The capsule has been developed to record images inside the gastrointestinal tract [120], [121].

The capsule robot is equipped with a wireless transmission device and an on-board camera. Hospitals have been using endoscope capsules since 2001 [122]. While this capsule traverse through a digestive tract, it captures images and transmits them through a wireless connection to a recorder which a patient wears on a belt. The main challenge with the capsule endoscope is, it cannot provide precise localization of disease areas [123].

TABLE 1. A of summary of applications and techniques for military.

Applications	Techniques and References
3D Object Detection [11] [12] [13] [14]	LiDAR [11], RADAR [12], FLIR[13] Neural Network Architectures [14] Camera and LiDAR fusion [14]
Data Fusion in WSNs [16] [6] [17] [18]	Energy Consumption [16] Probability theory [6] Fuzzy algorithms [17] Combination of Fuzzy and Neural Networks [18]
Military Image Captioning [19] [20]	Deep Learning [19] Language models [20]
Fusing Infrared and Visible Images [22] [21]	Different Resolution Total Variation (DRTV) [22] Multiple Level Fusion [21]
Object Detection [23] [24]	Statistical methods on hyperspectral imagery (HSI) [23] Deep Learning Techniques [24]
Target Tracking [25] [26] [27]	Deep Learning, Kalman filter [25] Hyperbolic Trilateration, fusion estimation covariance matrix [26] Geometry and ANN [27]

TABLE 2. A of summary of applications and techniques for robotics.

Applications	Techniques and References
Localization [36] [37] [38] [42] [43] [44] [45] [39] [40] [41] [46] [47] [48] [49] [50] [51] [50] [52]	Extended Kalman Filter [48], [40], [39] Kalman Filter [47] Deep learning [46] Hypotheses fusion [49] Unscented Kalman Filter [50] Dual Kalman Filter [51] Convolutional Neural Network [50] Long Baseline [52]
Self-positioning [37] [53] [54] [55] [56] [57]	Kalman Filter [53] Extended Kalman Filter [54] [55] [56] Recurrent Neural Network (RNN) [57]
Navigation and Obstacle Avoidance [58] [59] [60] [61] [62] [63] [64] [35]	Customized Fusion algorithms [59] A combination of Fuzzy Logic algorithms and Multisensor Technology [60] Customized methods [61] Integration of Fuzzy Logic and Neural Network [62] Fuzzy Control approach [63] Q-learning algorithm [64] Kalman filter [35]
Face and Hand Recognition [65] [3] [66] [67]	Neural network [65] Deep Neural Network and Transfer Learning [3] A Customized algorithm [66] A Customized algorithm [67]
Gesture or Gaze Control [68] [69] [70] [71] [72] [68]	Deep Reinforcement Learning [68] Customized algorithms [71] Support Vector Machine and Genetic algorithms [72]
Object Tracking [73] [74] [75] [76]	Kalman Filtering [73] Leader-Following approach [74] Neural Network [76]
Locomotion Tasks [77] [78] [79] [80]	Machine Learning methods [78] A customized approach [79] Neural Network [80]

To resolve the problem authors of [122] and [121] introduced a multi-sensor data fusion approach which is based on a particle filtering approach and a state-space model. Their prototype capsule is a magnetically actuated soft capsule endoscope designed for drug delivery and disease detection in the upper GI-tract. Further, the authors in [124] presented

TABLE 3. A of summary of applications and techniques for healthcare.

Applications	Techniques and References
Monitoring and Wearable Technology [81] [82] [83] [84] [86] [87] [88] [89] [90] [91] [92] [94] [95] [96] [93]	Fuzzy Set theory [81] A combination Sensor approach [82] Customized algorithm [83] Transfer Learning approach [86] Deep Learning approach [92] Hierarchical fusion algorithm [93] Fusion Model [96]
Wireless Body Sensor Networks [97] [98] [99] [100] [101] [102] [103] [104] [105] [106] [81]	Information Fusion Architecture [98] Extended Kalman Filter [99] A customized algorithm [104] Fuzzy Reference [105] Healthcare Framework [106] A customized algorithm [81]
Medical Diagnosis [107] [108] [109] [110] [111] [112] [113] [114] [115] [96] [116] [98] [81] [117]	Probability theory [107] Feature Extraction technique [108] Discriminant Correlation Analysis [109] Convolutional Neural Network (CNN) and Learning Machine. [110] Canonical Correlation Analysis (CCA) [111] A customized algorithm [112] [113] Deep Learning [114] A customized method [116] Fuzzy Set theory [81]
Medical Imaging [118] [119] [115]	Deep Learning [119] Discriminative Feature Encoding method [115]
Capsule Endoscope [120] [39] [122] [123] [122] [121] [124]	Extended Kalman Filter [39] Bayesion Filtering [122] Non-rigid map [121] [124]

a real-time intraoperative map fusion approach that combines magnetic sensor and vision-based localization to control capsule endoscope.

VI. SUMMARY

This section presents an overall summary of all applications addressed in this paper. Table 1, Table 2, and Table 3 summarize all used references along with their techniques. This taxonomy of domains, applications, and techniques highlights the importance of intelligence and information fusion in real world applications. It is worth to note that fuzzy, Neural networks, KF and its variants, are mostly used techniques in intelligence fusion. Readers and researchers can also use it as a quick reference of the main topics covered in this research work, and as a guide for the types of applications deployed in the selected domains.

The focus of this review is to introduce applications of intelligent fusion technology. The search process was conducted based on 8 keywords as presented in section C. We applied the top-down approach, in which we first identified the domains, followed by applications within the domains, and then techniques within the applications. The broad search keywords were used to allow us to cover a wide range of applications in the domains which make use of fusion technologies, rather than types of algorithms used for data or information fusion techniques. Thus, the shortcomings of this research are we do not get in-depth for each of the techniques or approaches presented in the summary Tables 1, 2, and 3 and, there are some important algorithms for fusion techniques such as SLAM (Simultaneous Localization and Mapping) algorithm and its variants which are mainly used in robot localization were missing out in this review. Also, the computational complexity of referenced algorithms is not reviewed because it requires a detailed technical comparison among different problem types in terms of input parameters used, the type of input, and output for each intelligence fusion problem. However, in our further research work, we will conduct a review to analyze and classify techniques for data and information fusion, and we will get into details of the algorithms used.

VII. CONCLUSION

This paper had successfully answered the main question of this systematic review and presented the most prominent applications within three identified domains namely military, robotics and healthcare. In the military domain, we had identified six main applications. These include 3D object detection, data fusion and wireless sensor networks, military image captioning and fusing infrared and visible images, object detection and target tracking. We discovered the most published works for the use of intelligence fusion is in the robotics domain, where we classified them into seven major applications. These include localization, self-positioning, navigation and obstacle avoidance, face and hand recognition, gesture and gaze control, object tracking, and locomotion tasks. The most used fusion technique in robotics is Kalman Filter and its variants. We also managed to gather and classify five major applications in the healthcare domains. Health applications include monitoring and wearable technology, wireless body sensor networks, medical diagnosis, medical imaging, and capsule endoscope. Our main contribution in this study is we are the first one to identify and classify major applications that make use of intelligence fusion in military, robotics and healthcare domains.

REFERENCES

[1] H. Boström, S. F. Andler, M. Brohede, R. Johansson, A. Karlsson, J. Van Laere, L. Niklasson, M. Nilsson, A. Persson, and T. Ziemke, "On the definition of information fusion as a field of research," Univ. Skövde, Skövde, Sweden, Tech. Rep., 2007.

[2] M. A. Abidi and R. C. Gonzalez, *Data Fusion in Robotics and Machine Intelligence*. San Diego, CA, USA: Academic, 1992.

[3] C. Fu, W. Sheng, F. Wang, F. Ye, Q. Liu, and Q. Jiang, "Research and implementation of fast identity registration system based on audio-visual fusion," in *Proc. IEEE 7th Annu. Int. Conf. CYBER Technol. Autom., Control, Intell. Syst. (CYBER)*, Jul. 2017, pp. 1442–1445.

[4] D. A. Sala, V. J. Brusamarello, R. De Azambuja, and A. Cangelosi, "Positioning control on a collaborative robot by sensor fusion with liquid state machines," in *Proc. IEEE Int. Instrum. Meas. Technol. Conf. (I2MTC)*, May 2017, pp. 1–6.

[5] D. L. Hall and J. Llinas, "An introduction to multisensor data fusion," *Proc. IEEE*, vol. 85, no. 1, pp. 6–23, Jan. 1997.

[6] H. Durrant-Whyte and T. C. Henderson, "Multisensor data fusion," in *Springer Handbook Robots*. Berlin, Germany: Springer, 2016, pp. 867–896.

[7] C. O. Sereati, A. D. W. Sumari, T. Adiono, and A. S. Ahmad, "Implementation knowledge growing system algorithm using VHDL," in *Proc. Int. Symp. Electron. Smart Devices (ISESD)*, Nov. 2016, pp. 7–10.

[8] B. Khaleghi, A. Khamis, F. O. Karray, and S. N. Razavi, "Multisensor data fusion: A review of the state-of-the-art," *Inf. Fusion*, vol. 14, no. 1, pp. 28–44, Jan. 2013.

[9] D. Moher, "Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement," *Ann. Internet Med.*, vol. 151, no. 4, Aug. 2009, Art. no. e1000097.

[10] A. Bajaj and O. P. Sangwan, "A systematic literature review of test case prioritization using genetic algorithms," *IEEE Access*, vol. 7, pp. 126355–126375, 2019.

[11] S. Kim, H. Kim, W. Yoo, and K. Huh, "Sensor fusion algorithm design in detecting vehicles using laser scanner and stereo vision," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 4, pp. 1072–1084, Apr. 2016.

[12] L. Bombini, P. Cerri, P. Medici, and G. Alessandretti, "Radar-vision fusion for vehicle detection," in *Proc. Int. Workshop Intell. Transp.*, Mar. 2006, pp. 65–70.

[13] S. Schneider, M. Himmelsbach, T. Luettel, and H.-J. Wuensche, "Fusing vision and LIDAR–Synchronization, correction and occlusion reasoning," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2010, pp. 388–393.

[14] A. Rovid and V. Remeli, "Towards raw sensor fusion in 3D object detection," in *Proc. IEEE 17th World Symp. Appl. Mach. Intell. Informat. (SAMI)*, Jan. 2019, pp. 293–298.

[15] M. Liang, B. Yang, S. Wang, and R. Urtasun, "Deep continuous fusion for multi-sensor 3D object detection," in *Proc. ECCV*. Munich, Germany: Springer, 2018, pp. 663–678.

[16] L. Li and L. Wei-jia, "The analysis of data fusion energy consumption in WSN," in *Proc. Int. Conf. System Sci., Eng. Design Manuf. Inf.*, Oct. 2011.

[17] D. Izadi, J. Abawajy, S. Ghanavati, and T. Herawan, "A data fusion method in wireless sensor networks," *Sensors*, vol. 15, no. 2, pp. 2964–2979, Jan. 2015.

[18] M. Collotta, A. Messineo, G. Nicolosi, and G. Pau, "A dynamic fuzzy controller to meet thermal comfort by using neural network forecasted parameters as the input," *Energies*, vol. 7, no. 8, pp. 4727–4756, Jul. 2014.

[19] S. Das, L. Jain, and A. Das, "Deep learning for military image captioning," in *Proc. 21st Int. Conf. Inf. Fusion (FUSION)*, Jul. 2018, pp. 2165–2171.

[20] P. Kuznetsova, V. Ordonez, T. L. Berg, and Y. Choi, "TREETalk: Composition and compression of trees for image descriptions," *Trans. Assoc. Comput. Linguistics*, vol. 2, pp. 351–362, Dec. 2014.

[21] J. Ma, C. Chen, C. Li, and J. Huang, "Infrared and visible image fusion via gradient transfer and total variation minimization," *Inf. Fusion*, vol. 31, pp. 100–109, Sep. 2016.

[22] Q. Du, H. Xu, Y. Ma, J. Huang, and F. Fan, "Fusing infrared and visible images of different resolutions via total variation model," *Sensors*, vol. 18, no. 11, p. 3827, Nov. 2018.

[23] C. Ke, "Military object detection using multiple information extracted from hyperspectral imagery," in *Proc. Int. Conf. Progr. Informat. Comput. (PIC)*, Dec. 2017, pp. 124–128.

[24] M. Zhang, H. Li, G. Xia, W. Zhao, S. Ren, and C. Wang, "Research on the application of deep learning target detection of engineering vehicles in the patrol and inspection for military optical cable lines by UAV," in *Proc. 11th Int. Symp. Comput. Intell. Design (ISCID)*, Dec. 2018, pp. 97–101.

[25] W. Mei, X. Feng, R. Yu, and D. Hu, "Deep visual detection-tracker for aerial target," in *Proc. Chin. Control Conf. (CCC)*, Jul. 2019, pp. 8658–8664.

[26] E. Martin-Gorostiza, M. A. Garcia-Garrido, D. Pizarro, P. Torres, M. O. Miguel, and D. Salido-Monzu, "Infrared and camera fusion sensor for indoor positioning," in *Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN)*, Sep./Oct. 2019, pp. 1–8.

[27] J. Stencek, "Geolocation of multiple emitters on data provided by ESM sensors," in *Proc. Int. Conf. Military Technol. (ICMT)*, May 2019, pp. 1–5.

[28] T. Turja and A. Oksanen, "Robot acceptance at work: A multilevel analysis based on 27 eu countries," *Int. J. Soc. Robot.*, vol. 11, no. 4, pp. 679–689, Aug. 2019.

[29] C. Schou, R. S. Andersen, D. Chrysostomou, S. Bøgh, and O. Madsen, "Skill-based instruction of collaborative robots in industrial settings," *Robot. Comput.-Integr. Manuf.*, vol. 53, pp. 72–80, Oct. 2018.

[30] A. Realyvásquez-Vargas, K. C. Arredondo-Soto, J. L. García-Alcaraz, B. Y. Márquez-Lobato, and J. Cruz-García, "Introduction and configuration of a collaborative robot in an assembly task as a means to decrease occupational risks and increase efficiency in a manufacturing company," *Robot. Comput.-Integr. Manuf.*, vol. 57, pp. 315–328, Jun. 2019.

[31] F. Wang, S. Jusoh, and S. X. Yang, "A collaborative behavior-based approach for handling ambiguity, uncertainty, and vagueness in robot natural language interfaces," *Eng. Appl. Artif. Intell.*, vol. 19, no. 8, pp. 939–951, Dec. 2006.

[32] S. Jusoh and H. M. Al Fawareh, "An intelligent interface for a housekeeping robot," in *Proc. 5th Int. Symp. Mechatronics Appl.*, May 2008, pp. 1–6.
[33] D. Paulius and Y. Sun, "A survey of knowledge representation in service robotics," *Robot. Auto. Syst.*, vol. 118, pp. 13–30, Aug. 2019.
[34] S. García, D. Strüber, D. Brugali, A. Di Fava, P. Schillinger, P. Pelliccione, and T. Berger, "Variability modeling of service robots: Experiences and challenges," in *Proc. 13th Int. Workshop Variability Model. Softw.-Intensive Syst.*, New York, NY, USA, Feb. 2019, Art. no. 8.
[35] C. Wang and D. Du, "Research on logistics autonomous mobile robot system," in *Proc. IEEE Int. Conf. Mechatronics Autom.*, Aug. 2016, pp. 275–280.
[36] S. Erfani, A. Jafari, and A. Hajiahmad, "Comparison of two data fusion methods for localization of wheeled mobile robot in farm conditions," *Artif. Intell. Agricult.*, vol. 1, pp. 48–55, Mar. 2019.
[37] V. Kubelka, L. Oswald, F. Pomerleau, F. Colas, T. Svoboda, and M. Reinstein, "Robust data fusion of multimodal sensory information for mobile robots," *J. Field Robot.*, vol. 32, no. 4, pp. 447–473, Jun. 2015.
[38] S. Huang and G. Dissanayake, *Robot Localization: An Introduction*. Atlanta, GA, USA: American Cancer Society, 2016, pp. 1–10.
[39] I. A. Ramgopal and P. Manivannan, "Development of multi-sensor data fusion technique for the automated bus rapid transport system," in *Proc. Int. Conf. Robot., Current Trends Future Challenges (RCTFC)*, Dec. 2016. pp. 1–6.
[40] D. Hetenyi, M. Gotzy, and L. Blazovics, "Sensor fusion with enhanced Kalman Filter for altitude control of quadrotors," in *Proc. IEEE 11th Int. Symp. Appl. Comput. Intell. Informat. (SACI)*, May 2016, pp. 413–418.
[41] S. Bohez, T. Verbelen, E. De Coninck, B. Vankeirsbilck, P. Simoens, and B. Dhoedt, "Sensor fusion for robot control through deep reinforcement learning," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Sep. 2017, pp. 2365–2370.
[42] G. Du and P. Zhang, "A markerless human–robot interface using particle filter and Kalman filter for dual robots," *IEEE Trans. Ind. Electron.*, vol. 62, no. 4, pp. 2257–2264, Apr. 2015.
[43] J. Pomárico-Franquiz, S. H. Khan, and Y. S. Shmaliy, "Combined extended FIR/Kalman filtering for indoor robot localization via triangulation," *Measurement*, vol. 50, pp. 236–243, Apr. 2014.
[44] H.-Y. Chung, C.-C. Hou, and Y.-S. Chen, "Indoor intelligent mobile robot localization using fuzzy compensation and Kalman filter to fuse the data of gyroscope and magnetometer," *IEEE Trans. Ind. Electron.*, vol. 62, no. 10, pp. 6436–6447, Oct. 2015.
[45] J. Simanek, M. Reinstein, and V. Kubelka, "Evaluation of the EKF-based estimation architectures for data fusion in mobile robots," *IEEE/ASME Trans. Mechatronics*, vol. 20, no. 2, pp. 985–990, Apr. 2015.
[46] Y. Qingmei and S. Jianmin, "A data fusion method applied in an autonomous robot," in *Proc. 27th Chin. Control Conf.*, Jul. 2008, pp. 361–364.
[47] M. Alatise and G. Hancke, "Pose estimation of a mobile robot based on fusion of IMU data and vision data using an extended Kalman filter," *Sensors*, vol. 17, no. 10, p. 2164, Sep. 2017.
[48] J. Felip, A. Morales, and T. Asfour, "Multi-sensor and prediction fusion for contact detection and localization," in *Proc. IEEE-RAS Int. Conf. Humanoid Robots*, Nov. 2014, pp. 601–607.
[49] D. Jeon, H. Choi, and J. Kim, "UKF data fusion of odometry and magnetic sensor for a precise indoor localization system of an autonomous vehicle," in *Proc. 13th Int. Conf. Ubiquitous Robots Ambient Intell.(URAI)*, Aug. 2016, pp. 47–52.
[50] L. Cheng, B. Song, Y. Dai, H. Wu, and Y. Chen, "Mobile robot indoor dual Kalman filter localisation based on inertial measurement and stereo vision," *CAAI Trans. Intell. Technol.*, vol. 2, no. 4, pp. 173–181, Dec. 2017.
[51] L. Wang, R. Li, J. Sun, H. Soon Seah, C. K. Quah, and L. Zhao, "Feature-based and convolutional neural network fusion method for visual relocalization," in *Proc. 15th Int. Conf. Control, Autom., Robot. Vis. (ICARCV)*, Nov. 2018, pp. 1489–1495.
[52] E. Devassykutty and G. Brink, "Evaluation of high precision localization approach for a fleet of unmanned deep ocean vehicles," in *Proc. 2nd Int. Symp. Comput. Sci. Intell. Control (ISCSIC)*, New York, NY, USA, 2018, Art. no. 35.
[53] K. Li, C. Wang, S. Huang, G. Liang, X. Wu, and Y. Liao, "Self-positioning for UAV indoor navigation based on 3D laser scanner, UWB and INS," in *Proc. IEEE Int. Conf. Inf. Autom. (ICIA)*, Aug. 2016, pp. 498–503.
[54] N. Yu and B. Zhang, "An improved hector SLAM algorithm based on information fusion for mobile robot," in *Proc. 5th IEEE Int. Conf. Cloud Comput. Intell. Syst. (CCIS)*, Nov. 2018, pp. 279–284.
[55] J. Choi, S. Kim, Y. Lee, T.-J. Kim, and H.-T. Choi, "Relative pose estimation of underwater robot by fusing inertial sensors and optical image," in *Proc. 11th Int. Conf. Ubiquitous Robots Ambient Intell.(URAI)*, Nov. 2014, pp. 204–208.
[56] Y. Wang, R. Xiong, H. Yu, J. Zhang, and Y. Liu, "Perception of demonstration for automatic programing of robotic assembly: Framework, algorithm, and validation," *IEEE/ASME Trans. Mechatronics*, vol. 23, no. 3, pp. 1059–1070, Jun. 2018.
[57] D. Luo, Y. Ma, X. Zhang, and X. Wu, "Multi-sensor fusion based robot self-activity recognition," in *Proc. IEEE-RAS 18th Int. Conf. Humanoid Robots*, Nov. 2018, pp. 1–9.
[58] S. F. R. Alves, J. M., H. Ferasoli, L. K. A. Rincon, and R. A. T. Yamasaki, "Conceptual bases of robot navigation modeling, control and applications," in *Advances in Robot Navigation*. London, U.K.: InTechOpen, Mar. 2012.
[59] M. Panicker, T. Mitha, K. Oak, A. M. Deshpande, and C. Ganguly, "Multisensor data fusion for an autonomous ground vehicle," in *Proc. Conf. Adv. Signal Process. (CASP)*, Jun. 2016.
[60] X. Mao, W. Li, C. Lei, J. Jin, F. Duan, and S. Chen, "A brain–robot interaction system by fusing human and machine intelligence," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 3, pp. 533–542, Mar. 2019.
[61] Y. Wang, J. Chen, X. Mai, S. Bi, Y. Cheng, and N. Xi, "Event-based planning and control for teleoperation of hot line work robot," in *Proc. IEEE 8th Annu. Int. Conf. CYBER Technol. Autom., Control, Intell. Syst. (CYBER)*, Jul. 2018, pp. 339–343.
[62] Z. Wang, "Robot obstacle avoidance and navigation control algorithm research based on multi-sensor information fusion," in *Proc. 11th Int. Conf. Intell. Comput. Technol. Autom. (ICICTA)*, Sep. 2018, pp. 351–354.
[63] M.-G. Lai, W.-T. Zeng, and C.-F. Juang, "Navigation for two fuzzy controlled cooperative object-carrying robots in concave maps with the consideration of dead-cycle problem," in *Proc. IEEE Int. Conf. Fuzzy Syst.*, Jul. 2016, pp. 1905–1909.
[64] Y. Zhang, X. Wei, and X. Zhou, "Dynamic obstacle avoidance based on multi-sensor fusion and Q-learning algorithm," in *Proc. IEEE 3rd Inf. Technol., Netw., Electron. Autom. Control Conf. (ITNEC)*, Mar. 2019, pp. 1569–1573.
[65] L. Ke, X. Chen, and Q. Du, "The research of single-sample face recognition based on wavelet image fusion," in *Proc. IEEE Int. Conf. Intell. Saf. Robot. (ISR)*, Aug. 2018, pp. 575–578.
[66] Y. Liu, Y. Li, X. Ma, and R. Song, "Facial expression recognition with fusion features extracted from salient facial areas," *Sensors*, vol. 17, no. 4, p. 712, Mar. 2017.
[67] R. C. Luo, Y. C. Wu, and P. H. Lin, "Multimodal information fusion for human-robot interaction," in *Proc. 10th Jubilee Int. Symp. Appl. Comput. Intell. Informat.*, May 2015, pp. 535–540.
[68] S. Lathuiliere, B. Masse, P. Mesejo, and R. Horaud, "Deep reinforcement learning for audio-visual gaze control," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Oct. 2018, pp. 1555–1562.
[69] J. Lobo and J. Dias, "Vision and inertial sensor cooperation using gravity as a vertical reference," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 12, pp. 1597–1608, Dec. 2003.
[70] M. Rucci and R. Bajcsy, "Learning visuo-tactile coordination in robotic systems," in *Proc. IEEE Int. Conf. Robot. Autom.*, vol. 3, Nov. 2002, pp. 2678–2683.
[71] H. Martin, J. Donaw, R. Kelly, Y. Jung, and J.-H. Kim, "A novel approach of prosthetic arm control using computer vision, biosignals, and motion capture," in *Proc. IEEE Symp. Comput. Intell. Robotic Rehabil. Assistive Technol. (CIRAT)*, Dec. 2014, pp. 26–30.
[72] F. Wang, K. Gan, C. Wu, and F. Bu, "Comparative study on gesture recognition using multiple kernel learning via multi-mode information fusion," in *Proc. IEEE 7th Annu. Int. Conf. CYBER Technol. Autom., Control, Intell. Syst. (CYBER)*, Jul. 2017, pp. 19–24.
[73] D. Y. Kim and M. Jeon, "Data fusion of radar and image measurements for multi-object tracking via Kalman filtering," *Inf. Sci.*, vol. 278, pp. 641–652, Sep. 2014.
[74] H.-W. Park and J.-S. Choi, "Fusion of laser scanner and camera using a direct drive gimbal for leader-following formation control," in *Proc. 11th Int. Conf. Ubiquitous Robots Ambient Intell. (URAI)*, Nov. 2014, pp. 269–270.
[75] S. Lee and J. Mcbride, "Extended object tracking via positive and negative information fusion," *IEEE Trans. Signal Process.*, vol. 67, no. 7, pp. 1812–1823, Apr. 2019.

[76] S. Wang and X. Zhang, "An approach for fall detection of older population based on multi-sensor data fusion," in *Proc. 12th Int. Conf. Ubiquitous Robots Ambient Intell.(URAI)*, Oct. 2015, pp. 320–323.
[77] D. J. Cech and S. T. Martin, "Locomotion," *Functional Movement Development Across the Life Span*. Amsterdam, The Netherlands: Elsevier, 2012, pp. 288–308.
[78] C. Kertesz, "Exploring surface detection for a quadruped robot in households," in *Proc. IEEE Int. Conf. Auto. Robot Syst. Competitions (ICARSC)*, May 2014, pp. 152–157.
[79] W. Bosworth, J. Whitney, S. Kim, and N. Hogan, "Robot locomotion on hard and soft ground: Measuring stability and ground properties *in-situ*," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2016, pp. 3582–3589.
[80] Z. Cao, Q. Xiao, and M. Zhou, "Distributed fusion-based policy search for fast robot locomotion learning," *IEEE Comput. Intell. Mag.*, vol. 14, no. 3, pp. 19–28, Aug. 2019.
[81] C. Habib, A. Makhoul, R. Darazi, and C. Salim, "Self-adaptive data collection and fusion for health monitoring based on body sensor networks," *IEEE Trans. Ind. Inf.*, vol. 12, no. 6, pp. 2342–2352, Dec. 2016.
[82] P. Mazurek, J. Wagner, A. Miekina, and R. Z. Morawski, "Fusion of measurement data from impulse-radar sensors and depth sensors when applied for patients monitoring," in *Proc. IEEE Int. Conf. Comput. Intell. Virtual Environ. Meas. Syst. Appl. (CIVEMSA)*, Jun. 2017, pp. 205–210.
[83] H. Aly and M. A. Ismail, "UbiMonitor: Intelligent fusion of body-worn sensors for real-time human activity recognition," in *Proc. 30th Annu. ACM Symp. Appl. Comput. (SAC)*, New York, NY, USA, 2015, pp. 563–568.
[84] Y. Mengüç, Y.-L. Park, H. Pei, D. Vogt, P. M. Aubin, E. Winchell, L. Fluke, L. Stirling, R. J. Wood, and C. J. Walsh, "Wearable soft sensing suit for human gait measurement," *Int. J. Robot. Res.*, vol. 33, no. 14, pp. 1748–1764, Dec. 2014.
[85] *Wearable Usage Will Grow by Nearly 60% This Year: Almost Two in Five Internet Users Will Use Wearables*, eMarketer Articles, New York, NY, USA, 2015. [Online]. Available: http://stratusmarketing.com/author/emarketer-articles-and-newsroom-posts/
[86] N. Hernandez, M. A. Razzaq, C. Nugent, I. Mcchesney, and S. Zhang, "Transfer learning and data fusion approach to recognize activities of daily life," in *Proc. 12th EAI Int. Conf. Pervas. Comput. Technol. Healthcare*, New York, NY, USA, 2018, pp. 227–231.
[87] S. Jusoh, "A survey on trend, opportunities and challenges of mHealth apps," *Int. J. Interact. Mob. Technol.*, vol. 11, no. 6, p. 73, Nov. 2017.
[88] R. Wright and L. Keith, "Wearable technology: If the tech fits, wear it," *J. Electron. Resour. Med. Libraries*, vol. 11, no. 4, pp. 204–216, Oct. 2014.
[89] P. Rashidi and A. Mihailidis, "A survey on ambient-assisted living tools for older adults," *IEEE J. Biomed. Health Inform.*, vol. 17, no. 3, pp. 579–590, May 2013.
[90] J. C. Yeo and C. T. Lim, "Wearable sensors for upper limb monitoring," in *Proc. Wearable Technol. Med. Health Care*, 2018, pp. 113–134.
[91] T. Tamura, "Wearable inertial sensors and their applications," in *Wearable Sensors*. Amsterdam, The Netherlands: Elsevier, 2014, pp. 85–104, doi: 10.1016/b978-0-12-418662-0.00024-6.
[92] N. Dawar and N. Kehtarnavaz, "Action detection and recognition in continuous action streams by deep learning-based sensing fusion," *IEEE Sensors J.*, vol. 18, no. 23, pp. 9660–9668, Dec. 2018.
[93] M. Guo, Z. Wang, N. Yang, Z. Li, and T. An, "A multisensor multiclassifier hierarchical fusion model based on entropy weight for human activity recognition using wearable inertial sensors," *IEEE Trans. Human-Mach. Syst.*, vol. 49, no. 1, pp. 105–111, Feb. 2019.
[94] A. Kamišalić, I. Fister, M. Turkanović, and S. Karakatič, "Sensors and functionalities of non-invasive wrist-wearable devices: A review," *Sensors*, vol. 18, no. 6, p. 1714, May 2018.
[95] M. J. Deen, "Information and communications technologies for elderly ubiquitous healthcare in a smart home," *Pers. Ubiquit Comput.*, vol. 19, nos. 3–4, pp. 573–599, Jul. 2015.
[96] Q. B. Dam, L. T. Nguyen, S. T. Nguyen, N. H. Vu, and C. Pham, "E-breath: Breath detection and monitoring using frequency cepstral feature fusion," in *Proc. Int. Conf. Multimedia Anal. Pattern Recognit. (MAPR)*, May 2019, pp. 1–6.
[97] C. Edwards. (Aug. 2018). *Remote Health Monitoring: Benefits Keeping Touch*. Accessed: Sep. 3, 2019. [Online]. Available: https://www.medicaldevice-network.com/features/remote-health-monitoring-benefits/attachment/remote-health-monitoring/
[98] A. He, J. Shen, Y. Wang, and L. Liu, "Research on the fusion model reference architecture of sensed information of human body for medical and healthcare IoT," in *Proc. 17th Int. Symp. Distrib. Comput. Appl. Bus. Eng. Sci. (DCABES)*, Oct. 2018, pp. 162–164.
[99] A. Al-Zaben and I. Arafat, "Estimation and compensation of a biomedical sensor's response delay using extended Kalman filter," in *Proc. 3rd Middle East Conf. Biomed. Eng. (MECBME)*, Oct. 2016, pp. 42–45.
[100] N. T. Trung and P. Hafliger, "A submicrowatt implantable capacitive sensor system for biomedical applications," *IEEE Trans. Circuits Syst., II, Exp. Briefs*, vol. 62, no. 2, pp. 209–213, Feb. 2015.
[101] M. Hesse, P. Christ, T. Hormann, and U. Ruckert, "A respiration sensor for a chest-strap based wireless body sensor," in *Proc. IEEE Sensors*, Nov. 2014, pp. 490–493.
[102] F. Lebepe, G. Niezen, G. P. Hancke, and T. D. Ramotsoela, "Wearable stress monitoring system using multiple sensors," in *Proc. IEEE 14th Int. Conf. Ind. Informat. (INDIN)*, Jul. 2016, pp. 895–898.
[103] M. Abu-Saude and B. I. Morshed, "Accessing differential measures with a conjugate coil-pair for wireless resistive analog passive (WRAP) ECG sensors," in *Proc. IEEE Int. Conf. Electro/Inf. Technol.(EIT)*, May 2018, pp. 0887–0891.
[104] A. R. Bhangwar, A. Ahmed, U. A. Khan, T. Saba, K. Almustafa, K. Haseeb, and N. Islam, "WETRP: Weight based energy & temperature aware routing protocol for wireless body sensor networks," *IEEE Access*, vol. 7, pp. 87987–87995, 2019.
[105] C. Habib, A. Makhoul, R. Darazi, and R. Couturier, "Multisensor data fusion for patient risk level determination and decision-support in wireless body sensor networks," in *Proc. 19th ACM Int. Conf. Modeling, Anal. Simulation Wireless Mobile Syst. (MSWiM)*, New York, NY, USA, Nov. 2016, pp. 221–224.
[106] L. Wang, W. Sun, Y. Chen, P. Li, and L. Zhao, "Multimode data fusion based remote healthcare framework," in *Proc. Int. Conf. Big Data Eng. Technol. (BDET)*, New York, NY, USA, 2018, pp. 1–6.
[107] D. Neumann, S. Grbic, M. John, N. Navab, J. Hornegger, and R. Ionasec, "Probabilistic sparse matching for robust 3D/3D fusion in minimally invasive surgery," *IEEE Trans. Med. Imag.*, vol. 34, no. 1, pp. 49–60, Jan. 2015.
[108] A. Hazarika, L. Dutta, M. Barthakur, and M. Bhuyan, "Two-fold feature extraction technique for biomedical signals classification," in *Proc. Int. Conf. Inventive Comput. Technol. (ICICT)*, vol. 2, Aug. 2016, pp. 1–4.
[109] A. Hazarika, A. Sarmah, R. Borah, M. Boro, L. Dutta, P. Kalita, and B. K. Dev Choudhury, "Discriminant feature level fusion based learning for automatic staging of EEG signals," *Healthcare Technol. Lett.*, vol. 5, no. 6, pp. 226–230, Dec. 2018.
[110] Z. Wang, M. Li, H. Wang, H. Jiang, Y. Yao, H. Zhang, and J. Xin, "Breast cancer detection using extreme learning machine based on feature fusion with CNN deep features," *IEEE Access*, vol. 7, pp. 105146–105158, 2019.
[111] A. Hazarika, L. Dutta, M. Barthakur, and M. Bhuyan, "Fusion of projected feature for classification of EMG patterns," in *Proc. Int. Conf. Accessibility Digit. World (ICADW)*, Dec. 2016, pp. 69–74.
[112] A. Moussavi-Khalkhali, M. Jamshidi, and S. Wijemanne, "Feature fusion for denoising and sparse autoencoders: Application to neuroimaging data," in *Proc. 15th IEEE Int. Conf. Mach. Learn. Appl. (ICMLA)*, Dec. 2016, pp. 605–610.
[113] C.-W. Huang and S. Narayanan, "Comparison of feature-level and kernel-level data fusion methods in multi-sensory fall detection," in *Proc. IEEE 18th Int. Workshop Multimedia Signal Process. (MMSP)*, Sep. 2016, pp. 1–6.
[114] L. Mao, N. Wang, L. Wang, and Y. Chen, "Classroom micro-expression recognition algorithms based on multi-feature fusion," *IEEE Access*, vol. 7, pp. 64978–64983, 2019.
[115] W. Li, Y. Yao, D. Ni, S. Chen, B. Lei, and T. Wang, "Placental maturity evaluation via feature fusion and discriminative learning," in *Proc. IEEE 13th Int. Symp. Biomed. Imag. (ISBI)*, Apr. 2016, pp. 783–786.
[116] C. Zhang, S. Mao, C. Wong, E. S. Hui, C. Ye, H. Li, J. Ma, and H. T. Ma, "A study of data fusion for Alzheimer's disease based on diffusion magnetic resonance imaging," in *Proc. IEEE 10th Conf. Region (TENCON)*, Nov. 2016, pp. 1019–1022.
[117] B. Hannan, X. Zhang, and K. Sethares, "IHANDs: Intelligent health advising and decision-support agent," in *Proc. IEEE/WIC/ACM Int. Joint Conf. Web Intell.(WI)*, Washington, DC, USA, vol. 3, Aug. 2014, pp. 294–301.
[118] A. P. James and B. V. Dasarathy, "Medical image fusion: A survey of the state of the art," *Inf. Fusion*, vol. 19, pp. 4–19, Sep. 2014.
[119] X. Liang, P. Hu, L. Zhang, J. Sun, and G. Yin, "MCFNet: Multi-layer concatenation fusion network for medical images fusion," *IEEE Sensors J.*, vol. 19, no. 16, pp. 7107–7119, Aug. 2019.
[120] S. S. Mapara and V. B. Patravale, "Medical capsule robots: A renaissance for diagnostics, drug delivery and surgical treatment," *J. Controlled Release*, vol. 261, pp. 337–351, Sep. 2017.

[121] M. Turan, Y. Almalioglu, H. Araujo, E. Konukoglu, and M. Sitti, "A non-rigid map fusion-based direct SLAM method for endoscopic capsule robots," *Int. J. Intell. Robot. Appl.*, vol. 1, no. 4, pp. 399–409, Dec. 2017.
[122] M. Turan, Y. Almalioglu, H. Gilbert, H. Araujo, T. Cemgil, and M. Sitti, "Endosensor fusion: Particle filtering-based multi-sensory data fusion with switching state-space model for endoscopic capsule robots," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2018, pp. 1–8.
[123] L. Liu, S. Towfighian, and A. Hila, "A review of locomotion systems for capsule endoscopy," *IEEE Rev. Biomed. Eng.*, vol. 8, pp. 138–151, 2015.
[124] M. Turan, Y. Almalioglu, E. P. Ornek, H. Araujo, M. F. Yanik, and M. Sitti, "Magnetic- visual sensor fusion-based dense 3D reconstruction and localization for endoscopic capsule robots," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Oct. 2018, pp. 1283–1289.

SHAIDAH JUSOH was born in Kedah, Malaysia. She received the B.Sc. degree (Hons.) in IT from Universiti Utara Malaysia (UUM), the M.Sc. degree in computer science from the University of Guelph, Canada, and the Ph.D. degree in intelligent system from the University of Guelph, Canada, in February 2006. During her Ph.D. degree, she also worked as a Seasonal Lecturer with the School of Engineering and the School of Computer Science, University of Guelph. After completed her Ph.D. degree, she joined the School of Engineering, as a Postdoctoral Fellow. She continued her teaching profession at UUM. She obtained several research grants from the Malaysia Higher Ministry of Education while teaching at UUM. She also joined several universities in Saudi Arabia, before joining Princess Sumaya University for Technology, in 2017, where she is currently the Chairman of the Computer Graphic and Animation Department. Her main research interests include intelligent systems, NLP, and HCI.

SUFYAN ALMAJALI (Member, IEEE) received the Ph.D. degree in computer science from the Illinois Institute of Technology, Chicago, IL, USA. He worked for several IT companies in USA, including the Director of Technology Solutions for Vertex, Chicago, the Chief Technology Officer with Secure Data Replicator, Chicago, where he supervised the development of an online real-time data replication system. He has 19 years of academic and industrial experience. He is currently an Associate Professor of Computer Science with Princess Sumaya University for Technology, Amman, Jordan. In addition to Princess Sumaya University, he taught at several universities in the states, including Chicago State University, Robert Morris University, DeVry University, and Benedictine University. His current research interests include the Internet of Things security, mobile edge computing, and network security.