A Survey on Multi-Sensor Fusion Techniques in IoT for Healthcare

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***Abstract*—In Internet of things (IoT) dedicated for healthcare, heterogeneous data can be gathered from different body sensors, environmental sensors and other data sources such as cameras, audio recorders, etc. The aggregation, synchronization, processing and fusion of these heterogeneous data are critical tasks to accurately provide real-time healthcare services. This paper provides a survey on different multi-sensor data fusion techniques in IoT for healthcare. Through focusing on decision-level fusion, the paper explains different advanced techniques such as machine learning that are needed for the integration of multiple healthcare data sources. Detailed comparisons of sensors used, healthcare applications, types of environment, accuracy metrics and results are discussed. In addition, we present observations and recommendations for researches who wish to work in sensor fusion for healthcare.**

I. Introduction

Based upon the advanced technologies of Internet of things (IoT), applications dedicated for healthcare are presented which are very emerging and necessary. Examples on applications applied for healthcare in IoT are: real-time activity monitoring, fall detection, abnormality detection, and diseases diagnosis [1], [2], [3], [4], [5], [6], [7]. These IoT healthcare applications demand the usage of wide range of heterogeneous sensors. The first type is the body sensors classified into biomedical and activity sensors. Biomedical sensors are mainly targeted to record the health and physiological vital signs of the patient. Activity sensors are any body worn devices that can help for determining the location, posture and position of the patient. Examples on body sensors are heart rate, blood pressure, Electrocardiography (ECG), Electromyography (EMG), gyroscope, etc. The second type is the environmental sensors for measuring the contextual environment around the patient. They can be mechanical, acoustic, optical, chemical, force, proximity and even imaging sensors. Examples are temperature, humidity, infrared, contact, cameras, etc. Multi-sensor fusion techniques are the techniques that combine several unrelated devices and sources of data to be processed together for better quality of services. Multi-sensor data fusion is presented to obtain better results from the aforementioned different sources [8], [9], [10], [11], [12]. These multi-sensor fusion approaches increase the reliability and robustness of the healtchcare systems by reducing the threatens posed by various malfunctions in the sensors and environment itself such as the power and communication [3]. In addition, global decisions can be taken based on the dependability between the data sources. Several surveys have been conducted on multi-sensor fusion techniques. A survey on multi-sensor fusion techniques in body sensor networks can be found in [13]. The authors categorize the fusion process according to the level where the fusion is performed: data-level, feature-level or decision-level. The authors focus on fusion of the sensors mounted on the body for the purposes of different applications including the recognition of activities and emotions, and general health. But how the multi-sensor fusion process affects the different healthcare applications is not tackled such as studying the influence of numerous techniques on the detection and diagnosis of diseases. Another survey paper in [14] discusses the data fusion mathematical methods. The authors focus on the probabilistic, artificial intelligence and evidence based methods for data fusion in applications including multi-target tracking, environmental monitoring and remote sensing without reviewing any techniques applied on healthcare applications. The authors discussed environmental challenges in IoT such as the distribution of the environment, heterogeneity and non-linearity and its affection on the process of data fusion. In [15], the authors propose a survey on data fusion in IoT in correspondence with the term context awareness. The authors categorizes the data fusion technique to three levels as reviewed in [13]. They propose explicit details of the advantages and limitations without referring to the application where the fusion technique is implemented. The paper in [16] proposes the state of the art of the data fusion techniques applied to the sensors settled in mobile devices. These techniques are distinguished to be suitable for the different constraints on the mobile devices such as the limited processing and power capabilities and also distinguished for working on specific sensors equipped in the mobile devices. The work in [17] presents ten parameters to evaluate sensor data fusion frameworks. Next, the authors focus on one of the proposed parameters "fusion complexity" to evaluate different proposed approaches for sensor fusion. Table I summarizes the related works addressing the topic of sensor fusion in IoT. Note that *NR* defines non reported results. This paper focuses on the state-of-the art in multi-sensor fusion techniques for healthcare applications including different medical applications and different medical diseases. This paper presents the effect of varying different factors on the quality of the healthcare application such as different categories of the techniques, the level where the techniques are applied and the types and number of sensors fused. The remainder of this paper is organized as follows. Section II provides an overview of multi-sensor fusion techniques for healthcare. Discussion and comparison are presented in section III. Finally, Section IV presents the challenges and future advancements.

TABLE I. COMPARISON OF RELATED WORK

Ref	Environment	Research target	categories surveyed
[13]	Body sensor network	Physical activity recognition Emotion recognition & General health	Data-level Feature-level Decision-level
[14]	Distributed, heterogeneous & nonlinear	Target tracking	Decision-level
[15]	Environmental and physiological sensors	NR	Data-level Feature-level Decision-level
[16]	Sensors in mobile devices	Identifying activities of daily living	Decision-level
[17]	Heterogeneous	Smart city application	Semantic technologies

II. Multi-Sensor Decision-Level Fusion Techniques for Healthcare

According to authors of [3], sensor fusion can be categorized into data-level, feature-level and decision-level. In data-fusion, the raw data coming from sensors are combined directly. In feature-level fusion, the features of the data collected from the different sensors are firstly extracted and then fusion technique are applied on the features for the purpose of combining them. On the other hand, decision-level fusion includes applying data mining, machine learning and computer vision techniques on the different decisions gathered from the processing of the individual sensors for the purpose of reaching a global decision. Several techniques of decision-level sensor fusion category are used in healthcare systems for multi-modal sensors including intelligent fusion based models, e.g. fuzzy logic based techniques, probabilistic and statistical based models e.g. Bayesian reasoning and Markov Decision Process and Dempster Shafer theory. Other models such as data mining based models and threshold technique based models also exist. The following sections focus on the methodologies of decision-level sensor fusion category.

A. *Fuzzy Logic- based Technique*

The fuzzy logic technique was introduced by the proposal of the fuzzy set theory in 1965 [8]. This technique is composed of three phases: the fuzzification for inputs, applying fuzzy rules to obtain the outputs and de-fuzzification of the outputs. When implementing the fuzzy logic technique for healthcare, the inputs to the fuzzy systems are a set of biological values or environmental sensors or both related to the patient. The outputs are soft decisions, which means the probabilities of the classification of the condition of the patient. The fuzzy system doesn't indicate whether the user is classified to specific class condition or not (hard decision) like clearly having a heart attack, asthma attack, etc, but it indicates the probability or the degree to which the patient is belonged to each of the conditions. For example, according to the heart rate and oxygen saturation values, the patient may be 60% suffering an Anemia and 10% having heart problems and so on. In [3], the authors monitor the healthcare of the persons in home by classifying the person's situation into two classes: normal or distress. The system is composed of few subsystems according to the set of sensors fused. The fuzzification step is performed separately on the different subsystems. The fuzzy inference engine contained a Mam-dani fuzzy methods for an output variable localization and also an output linguistic variable alarm. De-fuzzification is performed by applying the smallest value of maximum method on the resulting output alarm and applying the centroid of area for the localization output. This paper clarifies the flexibility of the fuzzy based techniques on how multiple outputs can be produced from the same system through applying different independent fuzzy rules. In [6], fuzzy logic is used but as a sub part of the proposed solution. This paper proposes a physiological sensor classification approach to classify the person mental status to either relaxed or stressed classes based on vital signs data collected from body sensors. The system is based on case based reasoning (CBR) technique for the classification of the individual sensor signals and then fuzzy logic is applied by performing the fuzzification for each extracted feature from each of the sensors individually. Defuzzification uses max method to get the similarity between the features. Weighted average is used to get second level similarity between two cases based on similarity of all features. The authors in [18] provide a healthcare system dedicated for asthma attack patients to detect the sudden worsening of asthma symptoms caused by the tightening of muscles around airways (bronchospasm). Each of the inputs are fuzzified into three fuzzy sets: low, normal and high. Then a Mamdani model is used for the inference engine with applying three rules. Defuzzification is done by assigning an output degree to three fuzzy sets: asthma attack, normal and severe asthma cough. The final output is generated by applying center of area method. In [19], a fuzzy set theory based system is designed for monitoring the patient's health, and emergency assessment and hence provides a decision output. This paper applies similar method to the aforementioned ones with the following differences: the fusion procedure is not continuously applied, but when only new criticality is detected by any of the sensors. Only then, the fusion is performed and a decision is taken based on the fusion procedure of all of the sensors readings. Therefore, the number of unnecessary taken decisions is eliminated. Other similar IoT healthcare systems depending on fuzzy logic fusion exist in [20], [19] and [21]. We can observe that fuzzy logic is an appropriate fusion technique used in healthcare systems. In healthcare IoT, such as ambient assisted living enviroments, data is collected from multi heterogeneous sensors. The different values of the sensors themselves together doesn't have enough sharp boundaries to classify a specific medical case or situation. This is because either the data is ambiguous and fuzzy or there are different decisions to be taken according to different combinations of the multi-sensors. Or even the data collected itself is imprecise or incomplete or have some level of uncertainty because of the nature of the data (physiological, acoustical..) and the nature of environment (usually wireless communications are used for data aggregation in BSN or IoT). Fuzzy logic based fusion techniques are simple in terms of computing complexity. They are also flexible because extra sensors can be integrated and new rules can be added and updated into the system after it is being built. This can be of great benefit when trying to enhance the accuracy of the system and reducing the error.

B. *Bayesian- based Technique*

Bayesian based fusion technique is built upon the Bayes' theorem [22], [23]. Unlike fuzzy logic based technique, the Bayesian method makes use of prior knowledge of the medical information and conditions of the patient to be able to classify new conditions. So, a learning phase is needed in this type of fusion technique. Bayesian theorem depends upon two types of probability functions; the prior probability which is calculated based on previously classified conditions and the likelihood probability which depends upon new feature values gathered from the sensors fused. Usually, the equation used for the calculation of the probabilities is:

$$p(C|A_1, ..., A_n) = \frac{1}{Z}p(C)\prod_{i=1}^{n} p(A_i|C) \tag{1}$$

where C is the condition to be classified, $p(C)$ is the class prior probability and $p(A_i|C)$ is the likelihood probability. A_1 through A_n are attributes variable values gathered from the sensors' data where n is the number of input sensors and Z is a scaling factor depends only on A_1 through A_n. In [9], the authors propose SPHERE (Sensor Platform for Healthcare in Residential Environment) multiple modalities system. The system builds a Bayesian model for classification known as the multi-class bayes point machine (BPM) described by three multi attribute decision models. They are the weighted and unweighted additive and fused switching models. The aim and target of [9] is location prediction and activity recognition of the patient. In [24], the paper proposes a system for remote monitoring of user physiological data. Besides, the method performs a body movement and fall detection for the patient. Naive Bayes classifier is applied to fuse the data collected from the accelerometers mounted on the body of the patient according to Bayesian equation described in equation 1. The technique is applied on a centralized manner which requires central processing device attached to the patient (smart phone). The authors later in [25] propose the wireless intelligent personal communication node (W-iPCN) into the system design flow to reduce the amount of processing workload on the android smart phone for the purpose of battery life conservation. The authors in [26] propose a similar approach to [24] based on dynamic Bayesian network for the purpose of assessment of the probability of fall risk. Dynamic Bayesian network is used because of the great dependences between the variables which are collected from multi-sensors employed in their research. The first phase continuously calculates the overall acceleration and as soon as potential fall risk is detected, the value is forwarded to a database along with the heart rate and Oxygen saturation. A naive Bayes algorithm is performed to detect the fall using the accelerometer value making use of the abnormalities of the heart rate and SpO2 in the fusion process. This result is further combined with the second phase of the system to increase the reliability of the final system and exclude false alarm events. The second phase applies DBN for monitoring of the activities of daily living (ADL) in accordance with the result from the first phase. Finally, the multi-sensor fusion process is done and the probability of fall alarm given any ADL is calculated using Bayes rule. It can be noticed that probabilistic models are usually used in healthcare systems that uses behaviors and actions of the patient as a part of the fusion of the data needed for the application. Applications presented in this subsection are mainly limited to fall detection and abnormalities detection while monitoring of the daily activities. The probabilistic models require a learning phase for the technique to behave correctly when applied so this adds a level of complexity to the technique. Bayseian method is adequate for on-line learning because the posterior probabilities of an observation at a time becomes the prior probability of the new observation. Bayesian method has the advantage of its simplicity and flexibility. New sensors can be added in some applications, but medical experience is needed to alter the probabilities assigned. Baysian methods are most powerful for small datasets so its scalability with large datasets and hence large amount of sensors need to be tested [27].

C. Markov Process- based Technique

Hidden Markov Model(HMM) is a generative probabilistic model used for generating hidden states from observable data. Using data gathered from different sensors (usually binary sensors in the HMM domain of the healthcare application which means that the sensor can be either on or off), an observable Markov model can be built. The model describes the sequence of the daily activities of the patient where each activity represents a state of the model. The idea is that the activities or locations of the patient are recorded and ordered separately by date such that the end-time of one activity/location is the start time of the next. The model can be used to detect when change occurs in the sequence of daily activities and also predict an observation sequence based on the current situation. This detection and prediction of the daily activity sequences is a huge factor when combined with other vital sign sensors and other environmental information for the purpose of emergency and abnormality detection case. The aim of the system in [28] is to detect behavioral and health-related changes of a person in assisted life living environment by detecting the abnormalities in daily activities. Detecting abnormalities helps to make diseases more predictable. The full approach is based on hidden markov model and fuzzy rule. The system is composed of some domains: daily activities, locations and vital signs. Daily activities and locations are fused using HMM. Vital signs domain's abnormality checking result is combined with the aforementioned results using a fuzzy rule-based model stored in the cloud database. This helps to make a high level conclusion decision for the detection of global abnormalities. The authors in [10] provide a similar approach for detecting the abnormalities in elderly people's behavior for the purpose of detecting possible dementia. They use and apply HMM which is based mainly on the data from passive Infra-Red (PIR) motion sensors. Two methods are used for the calculation of abnormality function for any new observation arriving which are distance measures Kullback-Leibler and log-likelihood methods. HMM is also a probabilistic model and like Bayesian model it is also usually used in healthcare systems that uses behaviors and actions of the patient as a part of the fusion of the data needed for the application. The authors recommend using HMM when the application is about modeling behavior based on discrete location e.g. monitoring of the daily activities. Unlike Bayesian method which is adequate for online learning, HMM enforces off-line learning only. HMM can best be applied to healthcare applications that contains sequential data where behaviors can be modeled using location based models or models that use physiological sensors as well. It has the advantage of the time aspect which means the generated probabilities are based on the measurements from the past also and not only the current physiological measurements. HMM suffers from high computation.

D. Demspter-Shafer Theory based Technique

Demspter-Shafer theory (DST) is a probabilistic method that deals with uncertainties in statistical models [29]. Applying DST as a fusion technique for IoT in healthcare can result in a good decision or conclusion with limited number of sensors data while being able to fuse heterogeneous data. Although it has high computational complexity, it is a flexible method. In this technique, the values of the input sensor is converted to a vector of the form

$$m\theta A = [m(\overline{A}), m(A), m(\overline{A}, A)] \quad (2)$$

where A represents the sensor being active, $\overline{A}$ nonactive and $(\overline{A}, A)$ imprecise. This is called belief mass function vector. After the value is multiplied by reliability factor resulting in probability value, a compatibility relationship between different vectors (sources of data) is searched e.g. the vectors corresponding to the same posture are fused. Finally, the global known Dempster's rule of combination is applied and a decision is taken according to the method used. In [11], data fusion based on the dempster Shafer theory (DST) for home healthcare monitoring is performed. The system aims at detecting the falls of the patient or the elderly at home. The technique is based upon motion input (including a doubt fall) and infrared sensor's data inputs to infer information about fall activity, posture and movement. This information are combined together to infer the location which helps in adding a certainty about the falling action. The falling result is highly related to the location where the person is doubted to have been fallen. The authors also add another model called DEN (dynamic evidential network) to their work to overcome the problem and effects of the non stationarity of sensors' data. Dempster-Shafer theory is a powerful technique in handling uncertainty. So, it is well suited in the healthcare applications (uncertainty of sensors' data as described above). Dempster-Shafer technique is close to the Bayesian technique in the way that weights or probabilities are assigned to the inputs after which a rule is applied to infer new probabilities which are further used for the new inferences. But Dempster-Shafer method assigns the weights also to the combination of inputs and not only the independent inputs. So, almost Dempster-Shafer is considered as a generalization of Bayesian method. In healthcare, one technique of them can be chosen according to the probabilistic information available about the input data. Noting that the overhead of the Dempster-Shafer is a limiting factor.

E. Thresholding Techniques and Others

Other sensor fusion methods rely on thresholding computations rather that model based techniques. Although these proposed papers are case and scenario based, they have to be considered into account when reviewing all the fusion techniques of the healthcare applications. In [5], the authors try to distinguish a fall of the patient from the activities of daily living (ADL). Centralized processing is performed after data is sent from wearable sensor and mesh network of sensor nodes in the home to a base station. The wearable node imply a possible fall to the reasoner layer through applying a thresholding algorithm. The algorithm aims for detecting four critical cases happening sequentially. If all the cases are considered a true, a data frame is sent to the base-station. On the base-station, the data from the mesh network is checked for confirming the fall according to the location of the patient reported by these sensors. An approach is presented in [30] for monitoring of the elderly suffering Alzheimer. The system can detect abnormal situations, possible falls and getting location. For the fall detection, an analytical method is used for determining the warning thresholds of the accelerometer empirically in a laboratory. Another algorithm is implemented and described for determining the location. In [31], the authors perform data fusion based on multi-tiered communication and a triadic hierarchical class analysis approach. A triadic hierarchical class analysis is based on a set-theoretical relations among objects and attributes. The objects and attributes are grouped into classes and then hierarchies of classes are constructed. Hence, a triadic context K is composed of three sets K1, K2, K3 and a ternary relation Y between them. The authors consider K1 as the object which is one of the sensors used. They apply two types of body sensors. K2 is considered as the time when the sensor value is recorded and K3 is considered as the location of the patient when recording the vital value. Using the relation Y, the triadic equivalent classes are grouped together into a hierarchic structure using a set of Hierarchical Class Analysis (HCA) rules. Finally, the knowledge is extracted from the hierarchy using an analyzer. Despite that their work lacks implementation details, simulation or case studies, the idea was novel.

III. Comparison of Decision-Level Fusion Techniques for Healthcare

The main metrics authors used for measuring the performance of the decision-level fusion techniques are: sensitivity, specificity, error rate and perfect classification. Sensitivity measures the proportion of positives that are correctly identified. In the healthcare domain, sensitivity means the ability of a test to correctly identify the status of the patient such as correctly reporting a disease, health condition, or falling in case of fall detection applications, etc. Whereas specificity measures the proportion of negatives that are correctly identified. Respectively in healthcare domain, it is the ability of the test to correctly identify those without the disease or not having specific health condition or not falling in case of fall detection applications. Perfect classification is one of the parameters that are used to validate a classifier and is defined as the number of correctly classified samples to the total number of samples [3]. While error rate is the number of wrongly classified samples to the total number of samples. A summarization of healthcare fusion techniques is presented in table II. The choice of the sensors differs according to the type of the disease and the type of application. Most of applications that perform health monitoring uses all the vital signs sensors, while applications that perform fall detection mainly depend on the posture sensors such as the tri-axial wearable accelerometer. On the other side, activity monitoring applications rely on environmental sensors such as optical and mechanical. The processing is mainly centralized in almost all of the proposed techniques where the data from the sensors are sent to the processing unit. The performance metrics shown in the table are guiding factors to compare the quality of different decision-level techniques. Table III lists the pros and cons of

TABLE II. SUMMARIZATION OF DECISION-LEVEL SENSOR FUSION TECHNIQUES IN HEALTHCARE

Ref	Technique	Application	sensors used	Sensitivity	Specificity	Implementation
[3]	Fuzzy logic	Healthcare monitoring of patient	Set of microphones, Wearable, Infrared sensors, Monitoring sensors	97%	NR	Both
[6]	Fuzzy logic	Classifying mental state of patient	Wearable {heart rate, respiration rate, oxygen saturation, finger temperature, carbon dioxide}	75%	100%	Real platform
[18]	Fuzzy logic	Detection of asthma attack	Wearable{heart rate, respiration rate, oxygen saturation}	NR	NR	Simulator
[19]	Fuzzy logic	Monitoring patient's health	Wearable{heart rate, respiration rate, temperature, systolic blood pressure}	NR	NR	Simulator
[24]	Baysian	Fall detection	Wearable accelerometer	87.5%	100%	Real platform
[25]	Baysian	Remote monitoring & fall detection	Temperature, Wearable{electrocardiography, accelerometer}	WEKA: 87.5% Real: 100%	NR	Both
[9]	Baysian	Location prediction Activity recognition	Passive infrared, Wearable accelerometer & Camera video	85%	94%	Real platform
[26]	Baysian	Fall detection	Wearable {accelerometer, heart rate, SpO2}, Environmental {PIR motion, door contact, pressure mats, power usage detectors}	90%	100%	Simulator
[28]	HMM	Detection of physiological abnormalities	Wearable vital-signs sensors, Environmental binary sensors	91.4%	NR	Real platform
[10]	HMM	Detecting possible dementia	Passive Infra-red, Wearable motion sensors	log-likelihood:94% Kullback-Leibler:100%	NR	Simulator
[11]	Dempster Shafer	Fall detection	Vital signs: RFPAT[32], Environmental: GARDIAN[33]	94%	100%	Real platform
[5]	Threshold technique	Fall detection	Wearable accelerometer, Environmental sensors { temperature, infrared motion, pressure, magnetic }	100%	NR%	Real platform
[30]	Threshold technique	Monitoring Alzheimer patients and fall detection	Motion sensors, Wearable patch, Anchor points	87.5%	98.7%	Real platform

TABLE III. COMPARISON OF DECISION-LEVEL FUSION TECHNIQUES IN HEALTHCARE

Technique	Pros	Cons
Fuzzy logic	• Deals with ambiguous input sensors • Flexible • Adaptable • Can be merged with other techniques (hybrid techniques) • Most used in monitoring and classification applications	• Doesn't handle the dependencies between the input senosrs
Bayesian	• Simple • Dependences between sensor inputs are allowed • Behaves better in multi-sensor inputs • Most used in fall detection applications	• Limited scalability • Requires prior knowledge of medical information
Markov Process	• Usually built based on binary sensor inputs (eliminating ambiguity, easy environment setup) • Most used in detection and predication of daily activities and abnormality detection	• High computational complexity • Usually combined with other fusion method for inferring the final decision
Dempster-Shafer based	• Deals with uncertainties • Works well with limited number of sensor inputs despite being heterogeneous	• Computational overhead increases proportional with number of sensors
Threshold technique	• Good results when applied to specific case • Can be applied in different applications	• Case based scenarios • Limited papers addressing healthcare domain

different decision-level fusion techniques in healthcare domain.

IV. CONCLUSION AND FUTURE ADVANCEMENTS

A Survey is conducted providing a full study and analysis of the different multi-sensor fusion techniques in IoT dedicated to healthcare, their requirements and best applications. Multiple techniques are discussed and categorized as fuzzy logic-based, Baysian-based, Markov process-based, Dempster-Shafer theory-based, and thresholding and other techniques. Usually, different sets of medical cases can be mapped to each of the above fusion techniques. The basic theory of each technique is explained along with examples on each implementation. Finally, an observation is conducted on each technique separately and on the mutual properties of combined techniques when exists. Multiple comparisons are proposed covering different aspects of the implementations. Examples are the sensors information, medical application, accuracy and the properties of the techniques. IoT for healthcare promises great benefits for the elderly despite that healthcare data fusion has the stringent requirements and challenges. The challenges arise from the nature of the healthcare domain in IoT. The material limits include battery shortage and limited wireless ranges. Technical limits such as the uncertainty of the data also exist. The uncertainty happens due to multiple reasons such as the sensor malfunction, corrupted data or misreadings which causes the ambiguity of the contextual information. So, the system robustness and reliability described as quality of service (QoS) in case of these different limitations is of a great challenge. Explicit challenges are the computational and communication costs of the technique deployed. In addition, the choice of the correct sensors to reduce energy consumption and computational complexity, and to reduce the false alarms or false results. So, providing an efficient sensor fusion technique that enhances quality of service while taking into consideration the aforementioned challenges is of a great importance. One possible solution is optimum exploiting of data required for the fusion technique by adapting the sleep cycles of the sensor nodes. The medical status of the patient will be a leading factor when designing that type of fusion technique. Finally, proposing hybrid fusion approaches that combine more than one technique that give good performance measures.

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