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Particle Swarm Optimization and Dempster Shafer Approach to Achieve Internet of Things Context Fusion Using Quality of Context

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Abstract

Context fusion is a very important aspect in a system that has to adequately simplify a required task in achieving context awareness in the Internet of things (IoT). IoT generates a large amount of data, which are massive, multi-source, heterogeneous, dynamic and sparse. Context information fusion is an important tool in the manipulation and management of these data in order to improve processing efficiency, provide advanced intelligence and increase reliability. Context information fusion can reduce the amount of data traffic, filter noisy measurements, and make predictions and inferences in any stages of data processing in IoT. As such when context is acquired from this domain, it has low confidence level due to reliability factors. In this paper Context information's reliability has been addressed through the use quality of context (QoC) by determining the combined confidence for acquired context from multiple sources. Particle Swarm Optimization selects the context information with the highest level of confidence and Dempster Shafer rule of combination fuses this context into more reliable information that can be used by the system to effectively adapt to changing context. From the obtained results the proposed solution indicates an improved fusion process with increased confidence.

***Keywords**: Context fusion, context awareness, Quality of Context, Internet of Things, Particle Swarm Optimization, Dempster Shafer Theory*

1. Introduction

The IoT paradigm provides a platform where a large collection of sensors, devices, applications and users give out context information. This information is in large volumes is mostly not error free and lacks reliability and credibility. For this information to be used for the intended purpose, it needs to be analyzed, fused and reasoned [1]. Therefore, context fusion is a vital process that accurately represents a situation, event, or action by a user. Context fusion is a process of consistently and usefully integrating context information acquired from various sources in order to provide a richer semantic of input data context. It is also required to increase the confidence of the fused context to bring new information and to give a complete view of the environment. As stated in [2], fusion of context information forms a unified picture or [3] a situation as a whole is greater than the sum of its parts.

The potential of context and context fusion in IoT cannot be over emphasized, as new context aware applications will lead to a whole new exciting future. On the World Wide Web (www), there is so much information that locating relevant information is near impossible to an average user of the web. In the transport sector, safety is critical and human error has contributed to many lives being lost. [4]. Object tracking and human

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activity identification are other processes that have a huge impact on how events can be accurately recognized. [5]

Another case with potential in IoT is path planning and environment monitoring. These aspects are influenced by a number of factors such as the time of day, the overall traffic patterns in the city (emergent behavior), weather conditions, constraints (such as variable speed limits in various sections of the path), conventions (such as driving slowly in a snowy day), user expediency, *etc.* All of the aforementioned constitute the context for the determination of the optimal path and knowing the environmental conditions.

These situations typical to the IoT domain will gather information and need to fuse it using one or more fusion schemes to achieve the desired goal. The key to achieving context fusion with any type of fusion method, for example, probabilistic (Weighted sum, Bayesian network) [6, 7] or logic/ontology based (Ontology, Fuzzy logic) [8, 9] is the evaluation of quality of input context to the fusion method. Quality assessment of context information and confidence using quality attributes increases the reliability and credibility of fusion context information.

In this paper we have looked at the rarely addressed quality assessment and fusion of context information through the use quality of context (QoC) by, first, determining the combined confidence for acquired context from multiple sources. Using Particle Swarm Optimization (PSO) to selects the refined context information with the highest level of confidence and Dempster Shafer rule of combination to fuse this context into more reliable information that can be used by the system to effectively adapt to changing context in the IoT domain.

The organization of this paper is as follows; in Section 2, we discuss the pertinent state of art works related to this study. In Section 3, we discuss confidence for QoC using context weighting, and QoC parameters. In Section 4 we discuss PSO, PSO context selection, Context Selection Optimization and Fusion Algorithm, fusion architecture, Dempster Shafer Combination Rule. In Section 5 we discuss simulated results and in Section 6 we make our conclusions and future works.

2. Related Work

Over the past decade, context fusion research works have been done and many provide valuable insights on context understanding, context awareness and indeed the realization of Internet of Things (IoT) domain specific applications. The following state of art works will be discussed to highlight the important contributions of context fusion.

A QoC based method for reliable fusion was proposed by [10] to address the fusion of uncertain context information in a pervasive environment. The authors proposed an uncertainty context fusion framework that would deal with quality of context management at all levels of the architecture. The architecture used three aspects in its management levels to protect and achieve high quality provision of fused context information to the context ware applications. The three aspects are threshold management, quality factor management and inconsistent context management. Under quality management, they looked at some quality measurement factors and defined context ontology to store the historical information contexts. With this the evaluation of raw, duplicate and inconsistent context was done to better contexts fusion. Their experimental context information was location acquired through the use of wireless sensor networks (WSN) and was used in the Internet of Vehicles (IoV) application. To realize accurate precision of the location context in real time, they used adaptive reasoning and reliable fusion. Our research uses concrete or refined context information for the fusion process in which all objective QoC parameters were taken into account to come up with combined confidence that give credibility to all contexts acquired.

Context information may have conflicts because of the distributed nature of sensors. Authors of [11] proposed an approach that could resolve context. Context information was categorized into two; internal and external contexts. Using such context without identifying the quality would pass conflicting information after fusion. They used to quality indicators to resolve conflicts in context, probability of correctness and trustworthiness. The research was motivated by how performance and reliability could be improved in context aware decision making systems using QoC indicators. According to the authors internal and external context conflicts were defined as follows; "internal conflict is the context conflict/inconsistency that may occur by fusing two or more context elements that characterizes the situation from different dimensions of a same observed entity in a given moment while external conflicts is the context conflict/inconsistency that may occur between two or more collected context data that describe the situation of an observed entity from the same point of view." This approach dealt with the conflict of context using only two aspects; Probability of correctness and trustworthiness. The use of only two attributes of quality does not provide a comprehensive way of dealing with context information reliability. Our approach increases the factors so that all aspect of quality are included to determine quality of context.

Context fusion was also used to analyze a target object on its current and future movements as it moves in an environment to determine whether a certain path through a terrain area is possible for a given type of vehicle. The authors of [12] used the terms driveability or trafficability to come up with a method to analyze how an object could assess its environment. The proposed method analyzed geographical information as context for decision making in the command and control systems. The quality attribute they concentrated on was resolution; an entity that used to measure the accuracy of the sensor data. Driveability factors that constituted the terrain and vehicle properties were fused together to determine if the vehicle could easily pass. Our work uses many quality of context attributes to handle the reliability of context information unlike driveability analysis that only considered resolution to measure certainty.

Authors of [13] used context fusion to estimate reliability on the sensor contextual data. The inherent ambiguity and inaccuracy of context information that was sensed from the noisy environment was represented, analyzed and reasoned by using a model developed using dynamic Bayesian Networks and Fuzzy-Set theory to deal with the reliability and confidence of context sources. This approach used probabilistic context fusion to increase the fusion confidence in the sensed contextual information. This research provided important information on fusion but was not specific on the quality attributes used to determine reliability. Our research uses specific QoC parameters to determine reliability and refinement for fusing of context information using the PSO and Dempster Shafer Theory.

Sensor Fusion using different theories and algorithms has been addressed by many researchers. [14] addressed sensor fusion by looking at the relationship between Weighted Dempster-Shafer Theory and the classical Bayesian method. The approached used tracking of a user's focus multiple sensor information. The system used a layered and modular approach to fuse sensed context information. The layers for the system separated the context information from the sensor so that the fusion process used only the perceived information. In this research the emphasis was on the fusion process for perceived context unlike our approach that fuses refined context information.

In [15] a middleware design for context ware fusion using privacy in emergency medical services was discussed. They devised a platform where data fusion was used to assist medical personnel in a health care environment to reduce privacy risk. The proposed design centered its focus on how privacy of users could be enhanced in context aware information fusion in the ubiquitous environment. Privacy is one of the quality attributes of context and sole use does not bring reliability to the fused information. Our research uses more parameters to determine the quality of context.

The degree of confidence notion was proposed by [16] and was used to build a combined framework of using logic and probability theory. This framework used merged confidence from associated experts to model beliefs as binary prepositions. They implemented an autonomous mobile robot that performed a sensor-based mapping within a building to test the framework. The indoor environment was partitioned into grids and context was obtained by the of use sensors within grids. This context was used to determine which partition grid was occupied by taking the sensor values as probabilistic contexts. And without using any reasoning methods occupancy of grids was achieved. The associated confidence of the sensor values was obtained through getting beliefs from experts and combining these beliefs to determine how the autonomous mobile robot could detect occupancy for any grid. Our research uses combined confidence of QoC to determine which context to use in the fusion process.

Chen and others [17] developed directed acyclic information graphs to fuse context information on a network. It used selected distributed context information from distributed sources to perform a customized fusion process using data fusion operators. The implementation was done by applications using inferred values from various sensors. This inherently incomplete and error prone context was aggregated by application to increase the reliability of the computed context. Using machine learning techniques, an algorithm was developed to perform a simple context fusion using historical context information. It is the fused context information that applications used to perform their different activities.

The aim for implementation of the system was to provide a system that meets application needs in a flexible and scalable way. The system, called, Context Delivery Network, connected multiple sources and sinks for information in order to deliver application specific data fusion functions. Fusing incomplete and error prone context information does not necessary produce more accurate context information. Our approach is to determine the quality of the context information even before the fusion process occurs. Reliability is achieved more by taking advantage of QoC and the fusion process.

In [18]**,** a framework for context aware systems using a data fusion approach was proposed. In this model, the functionalities to organize and specifically describe the interests of application in terms of context needs were envisaged. These processes had operations and information flows from various sensors and devices to the individual applications. The basic building block for the model was context from a set of representational domains that contained common functions. The results of these building blocks were later aggregated to form the desired functional blocks. The functional block was built on the understanding that information flows and functions of applications were the basis for building interoperable context aware software modules. This framework never considered the quality of information from the different domains before building software modules that could aggregate the acquired information.

The authors of [19] developed an application that used situational context information to recognize road signs. The approach fused the obtained digital maps and perceived situation context to identify road signs. Sensor reliability was achieved through the Dempster Shafer fusion process. The fusion process was such that the images captured by the camera were combined with the digital map to differentiate between road sign states; this sign, other sign, uncertain and no sign. The implementation showed an increased recognition of road signs with minimal error. Our research fuses only refined context information using the Dempster Shafter approach, which increases the reliability of perceived situational context information.

3. Confidence for Quality of Context

Combined confidence calculation is critical to our research and is obtained by taking into consideration all aspects that affect context information and is defined as "the measure of confidence in the measured context information as provided by the context object."

Since the IoT environment is dynamic with an ever increasing amount of context information, context information acquisition needs to be standardized. To standardize the collection and measurement of context information, every argument that affects context information was taken in account and used into calculating the combined confidence of the context. The measured and collected context was classified into two aspects; context weighting and QoC value.

Confidence of context has been calculated mainly on specific QoC parameter under consideration such as, usability, updateness, completeness. The importance of the QoC parameter used depended on the application needs. But the IoT environment has more contexts with different usage and importance. So using individual QoC parameter to calculate confidence of the quality of sensor data cannot suffice for IoT application needs. For example an application that uses a QoC parameter like updateness to select a context object may end up using low values in other parameters. Therefore, to cater for every application needs in the IoT environment, our approach uses combined confidence calculated from all QoC parameters and Context weight. The context weight is used to indicate the importance of the sensed data applicable to other context aware applications. The weighting of the contexts adds an important dimension to the quality parameter by attaching a weight to the sensor data in reference to the expected value. This is gives a true state of the quality of the context object in question.

3.1 Context Weighting

The context weighting value was determined by rating of closeness for the measured context value in providing discrimination based on the expected value of interest and has a range of [0,1]. As sensor readings are obtained, they are weighted proportionally to the variances for the expected and expected variable values using equation 1;

$$\omega_i = \frac{1}{\delta_i^{\gamma}} \tag{1}$$

Where ω is the weight, δ is the variance and γ the mean. In this way less weight is given to the sensor values with less precise measurement compared to the actual and more weight to measurements that are closer to the actual.

The algorithm dynamically assigns weights as sensor readings are acquired. The closer the measured value is to the actual the closer its value is to 1. A zero (0) value is an indicator that the value is invalid and cannot be used to calculate confidence.

3.2 QoC Value

Our study takes into account all the objective parameters of context because they measure the degree of conformity of the IoT environment as perceived by the measuring device. Let the sensed data value be the context object CO. The following parameters were used to calculate the QoC value; Up-to-Dateness, Trust-Worthiness, Completeness, Significance, Precision, Certainty, Validity, Usability, Accuracy, Access Right and Representation Consistency. The description and formula for each parameter is given as follows;

Up-To-Dateness is a quality that measures the validity of context information as given by the context object *(CO)* at a given time.

$$Age(\text{CO}) = t_{curr} - t_{meas}(\text{CO}) \tag{2}$$

Where Age (CO) is the lifetime of that context object, t_{curr}, is the current time and t_{meas}(CO), the measurement time of that context object (CO) uptodateness is given as

$$U(CO) = \left\{1 - \frac{Age\ (CO)}{Lifetime(CO)} \quad \text{if } Age(CO) < \ lifetime(CO) \text{ otherwise } CO \right. \tag{3}$$

Trust-Worthiness is a quality parameter that measures the correctness of information in a context object. Trust-worthiness of a context object is highly affected by the space resolution, *i.e.*, the distance between the sensor and the entity.. Let the accuracy of the sensor data be δ. The trust-worthiness, T (CO), of context object CO is defined by Equation

$$T(CO) = \left\{\left(1 - \frac{d(S,\varepsilon)}{d_{max}}\right) * \delta \quad \text{if } d(S,\varepsilon) < \ d_{max} \text{ otherwise } 0 \right. \tag{4}$$

Where d(S, E) is the distance between the sensor and the entity. d_{max} is the maximum distance for which we can trust on the observation of this sensor. δ is accuracy of a sensor as measured on the basis of a statistical estimation

Completeness is a quality measure that indicates the quantity of information that is provided by a context object. Completeness is the ratio of the number of attributes available to the total number of attributes. Completeness, C(CO), of context object CO is evaluated by Equation

$$C(CO) = \frac{\sum_{j=0}^{m} \omega_j\ (CO)}{\sum_{i=0}^{n} \omega_i\ (CO)} \tag{5}$$

Where m is the number of the attributes of context object CO that have been assigned a value and w_j(CO) represents the weight of the jth attribute of CO that has been assigned a value. Similarly, n is the total number of the attributes of context object CO and wi(CO) represents the weight of the ith attribute of CO.

Significance is quality measure is the ratio of context information to maximum critical level that type of context information can have and calculated by the equation

$$S(CO) = \frac{CV\ (CO)}{CV_{max}(CO)} \tag{6}$$

Where CV (CO) is the critical value of the context object CO and CV_{max}(CO) is the maximum critical value that can be assigned to a context object of the type that is represented by CO.

Precision is a quality parameter that indicates the exactness by which a context object CO can measure context information and is given by the equation

$$P(CO) = \frac{P_{curr}}{P_{max}} * Pr_{accuracy} \tag{7}$$

Where P_{curr} is the current precision, P_{max} is the maximum precision and $Pr_{accuracy}$ is the known exactness.

Certainty is a quality measure parameter that measures reliability of a context object in obtaining context information and is determined by the reply request and response requests. The equation for certainty is given as;

$$Ce\ (CO) = \left\{ C(CO) * \frac{N_j + 1}{N_i + 1} \quad \text{if} \quad F(CO) \neq 0 \text{ and } CO \neq 0 \text{ then } Ce(CO) = \frac{N_j}{N_i + 1} \right. \tag{8}$$

Where N_j+1 is the number of the reply requests, N_i+1 is the number of sending requests, C(CO) is the Completeness and F (CO) is the freshness. Freshness is equivalent to Age (CO) and it measures the time that elapses between reading the sensor value and delivery.

Validity is a quality parameter that measures how context information accurately corresponds to the expected value and is given by equation

$$V(CO) = \frac{\text{QualityValueGoal}}{\text{ActualQualityValue}} \tag{9}$$

Where QualityValueGoal is the expected value and ActualQualityValue is the measured value.

Usability is how much that piece of context information is suitable for use with the intended purpose. It considers the level of granularity of collected context information with the required level granularity.

$$U(CO) = \begin{cases} 1: \text{if Granularitylevel}(CO) \\ \geq \\ \text{granularitylevel (CR)} \\ 0: \text{otherwise} \end{cases} \tag{10}$$

Accuracy is a quality measure is given as:

$$A(O) = \frac{\text{CorrectnessProbability}}{\text{MinimumCorrectnessProbability}} \tag{11}$$

Where CorrectnessProbability is the current correctness probability of context and MinimumCorrectnessProbability is the minimum correctness probability according to the expected value.

Access Right is a quality measure that defines whether the context information provided by the context object has level of authorization to modification by other context objects. This attribute compares the access level of the context object to the access level of the context consumer.

$$AR(CO) = \begin{cases} 1: if\ AccessLeve(CO) \\ \geq \\ Accesslevel\ (CR) \\ 0: otherwise \end{cases} \tag{12}$$

Representation Consistency is a quality measure that indicates the ratio of representation format of actual context information to the expected context information as given by the context objects and is shown in equation.

$$RC\ (CO) = \frac{Expected(CO)}{Actual(CO)} \tag{13}$$

3.3 Combined Confidence for Quality of Context

Combined Context Confidence for the above QoC parameters is derived from the given QoC parameter set and parameter weight. It measures the confidence in the QoC parameters provided in the domain set. Context confidence is determined by applying the context quality weight and the actual value measured by the sensing device. The combined confidence is given by the following equation;

$$Cf\ (CO)_{conf} = \sum_{i=0}^{n}(Cf_{act}) * \ \ C(CO)_{QoC}$$

(14)

$$where\ 0 \leq \ C(CO)_{QoC}, Cf_{act} \leq 1$$

Where Cf $(CO)_{conf}$ is the combined confidence of the context object with reference to quality

$C(CO)_{QoC}$ is the calculated quality value for the QoC parameter of the measured low level context as given in the 3.2 section. Cf_{act} is the weight for the context information as shown in equation 1.

The context weight for each context object is evaluated and quantified according to the context object contribution to the IoT situation under consideration. The weight value ranges between 0 and 1. If the weight is closer to one then there is an attached importance for the context object to the associated event. The value of $Cf\ (CO)_{conf}$ accumulates over a given set of quality of context parameter domain and is equivalent to ∂ in equation 17.

4. Particle Swarm Optimization (PSO)

PSO has been used over the decades in solving computational problems by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO was originally intended for stimulating social behavior as a stylized representation of the movement of organisms in bird flock or fish school [19]. The algorithm was simplified and was used for optimization. A basic variant of the PSO algorithm works by having a population (called a swarm) of candidate solutions (called particles). The basic PSO algorithm can be described mathematically by the following equations:

$$\upsilon_{ij}^{t+1} = \omega\upsilon_{ij}^{t} + c_1 r_1^t(\rho_{ij}^t - \psi_{ij}^t) + c_2 r_2^t(\rho_{kj}^t - \psi_{kj}^t) \tag{15}$$

and

$$\psi_{ij}^{t+1} = \psi_{ij}^{t} + \upsilon_{ij}^{t+1} \tag{16}$$

Where c_1 and c_2 are positive learning rates constants, r_1 and r_2 are random functions in the range [0, 1]; ω is a inertia weight ψ_i is the position of the particle in a problem space with D dimensions; υ_i is the rate of change of position (velocity); ρ_i is the best previous position of the swarm; the index g indicates the best particle among all the particles in the population; and t indicates the iteration number. These particles are moved around in the search-space according to a few simple formulae. The movements of the particles are guided by their own best known position in the search-space as well as the entire swarm's best known position. When improved positions are being discovered these will then come to guide the movements of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered. Apart from a continuous version of the PSO, a binary version can be used in binary search spaces. This was proposed by [20] to represent velocities of particles as probabilities in the range [0..1]. This is the version that our research has adopted in the selection process of context.

4.1 PSO Context Selection Using Qoc Combined Confidence

Imperfect context information can cause derived contexts to be inaccurate. The erroneous context information should be sieved out to avoid corrupting the decision process. It is desirable to remove erroneous sources at the earliest possible stage to minimize adapting wrong context. Context selection from the vast IoT domain uses the PSO algorithm to find the near optimal value for a context object with a highest confidence value. Each context object that is sensed within the domain can be a possible value but we know that context reliability has many other aspects to be considered. To select a context object with most reliable value using the QoC confidence PSO is defined as follows;

$$CS(CO)_{i,j} = \frac{{\varphi_{i,j}}^{\delta}}{\sum_{j=1}^{n} {\varphi_{i,j}}^{\delta}} \tag{17}$$

Where $CS(CO)_{i,j}$ is the selected context object from given vector [i,j], ∂ is the confidence value used as the selection criteria, and φ is the actual sensed value of context object. Each context object has the calculated ∂ using the QoC parameters for the context value obtained. The algorithm runs to select the desired context object.

For the PSO to perform the selection of the required context object, it was extended to deal with binary data. The context object to be selected is done through an iterative selection process with each iteration marking the selected context object. This process continues until a defined number of selected context objects is reached. Each selected context object is given a probability value proportional to the real value calculated in Equation (16) limited to the interval [0, 1].

This section discusses the Context selection and fusion algorithm as shown in flow chart Figure. 1. The PSO algorithm performs optimization in continuous, multidimensional search space and IoT is a typical space. Our algorithm starts by the initialization process of the data in the search space. Each context value is a seen as a ‘particle swarm’ with its own velocity. The data set contains context objects which are all candidates in the selection process. To select the best context objects, two independent processes of weighting and QoC valuation are performed. The result is used to calculate the combined confidence which is the selection criteria for the context object. PSO uses this criteria and PSO update operator as constraints in the search process. The resultant set of selected context objects are fused using the Dempster Shafer rule of combination context into more informative information that can be used by the system to effectively adapt to changing context. The fused context objects are displayed at the end of the algorithm.

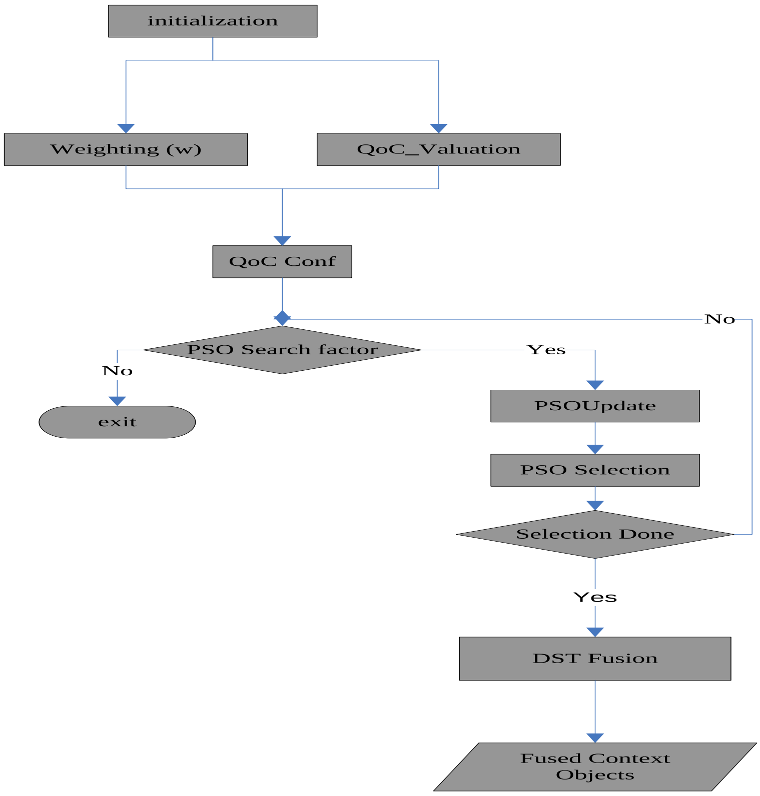

Figure 1. Context Selection and Fusion Flow Chart

4.2 IoT Context Selection Optimization and Fusion Algorithm

Input: objective function, QoC Parameters Contraints, IoT Context object, Context Object weight
Process: context object selection, QoC constraints calculation, combined confidence, DST fusion
Output: Fused **r**efined context objects.

1. *Initialize CS[i,j] = 0, CO=0, S[x]=0; QoC_P=0; QoC =0, Cf=0;CS(CO[I,j])=0;*

2. *Initialize data set ds[i,j]= [0,0]*

3. *Populate data set*
   For all i
   For all j Read in
   CO [i,j] ← rand ds[i,j];

4. *For all QoC-P read in all attri ← S[x]*

5. *For each QoC_P, Cal QoC*
   QoC ← Function(Qoc_P, attri)

6. *Rate Context Object*
   For each CO[i,j] := [1/∂ [pow]y];

7. *Cf ← Summation (CO[I,j])* [1/∂ [pow]y]*

8. *For all CO[i,j] getsum*
   SumCf ← Summation (CO[I,j].Math[pow]Cf)

9. *CS[I,j] ← CO>Math[pow]Cf/SumCf;*

10. *If ds [I,j] > 0 and Cf (CO[i,j]) > ds [i,j] then*
    CS (CO[I,j]) ← ds [i,j]

11. *δ := Cf;*

12. *for CS (CO[I,j]) := 1 to ds[i,j]*

13. *begin getprod*
    sumProd ← CS (CO[i,j]) CS (CO[i+1,j+1])*
    Bel ← δ sumProd*
    Pal ← 1 – Bel
    Fus ← Bel/Pal end;
    $m'_1 \oplus m'_2\left(CS(\mathrm{CO})_{i,j}\right)$ *:= fus;*
14. *Return* $\boldsymbol{m'_1 \oplus m'_2\left(CS(\mathrm{CO})_{i,j}\right)}$

In line 1 and 2 the initialization of objective function CS (i,j), Context Object CO, Context Source S, QoC_P, QoC, confidence function Cf and the data set is done. CS [i,j] is the objective function used for the PSO selection optimization. CO is the value of the context information as acquired by the context source, S[x]. Context information acquired has quality attributes QoC_P which are used to calculate quality of context QoC from the given data set ds[i,j]. Confidence function Cf defines the function used to calculate the combined confidence for all the QoC parameters. Initially all functions and variables will have zero.

In line 3 the population of the data set is set and values are read as context object to be used for selection although our research used a randomly generated data set.

In line 4, various attributes for the context information are read and assigned values. The following are the attributes from the context source S[x]; the context object age, context object lifetime, current time, Measured time, distance between the sensor and the entity, maximum distance to trust the sensor reading, sensor accuracy, number of attributes of the context object, total number of attributes of the context object, critical value for the context object, maximum critical value to be assigned to the context object, current precision, maximum precision, number of reply request, number of sending requests, quality goal value, actual quality value, granularity values 0 or 1, correctness probability, minimum correctness probability, access right level 0 or 1, context consumer consistency, context producer consistency.

In line 5, the Quality of context QoC for each context object is calculated by its unique function using the attributes obtained in QoC_P

In line 6, each context information value is rated according to the dimension of closeness to the expected value and a weight is assigned.

In line 7 and 8, using the weight and QoC for the individual context object, the combined confidence is calculate and stored in sumCf.

In line 8, 9, and 10, the objective function is used to select the desired refined context object from the data.

In line 11, the combined confidence of the selected context objects is assigned to a variable δ and line 12 is loop statement for the DST combination rule.

Line 13 is the block statement where the refined context objects are fused and display in line 14.

4.3 QoC PSO Context Refinement and Fusion Architecture

The implementation process of context refinement was achieved by taking the available or generated context information by context objects through a well-defined structure. The major aim of context refinement is to obtain concrete information by evaluating the information using its attributes and attaching the result of this evaluation to the context object. As shown in figure 1, our research was centered on extending the context information to express its reliability and conformity to application and user relevance through QoC attributes like accuracy, trustworthiness, usability *etc*. The general overview of context information refinement incorporates QoC parameter assessment and assignment, context weighting and combined confidence calculation, and selection. These processes ensure only the most reliable context information is selected as demanded by the applications, devices and other applications within the IoT domain.

The QoC PSO context refinement architecture figure 1 uses a multi stage process to refine raw context information to concrete context information. The raw context information is obtained from the IoT domain devices, applications, users and sensors. This is the imperfect context information that is shown as raw context (context_1, context_2 ….context_n). The raw context goes into the three (3) assessment phase; context weighting, QoC Assessment and QoC Assignment.

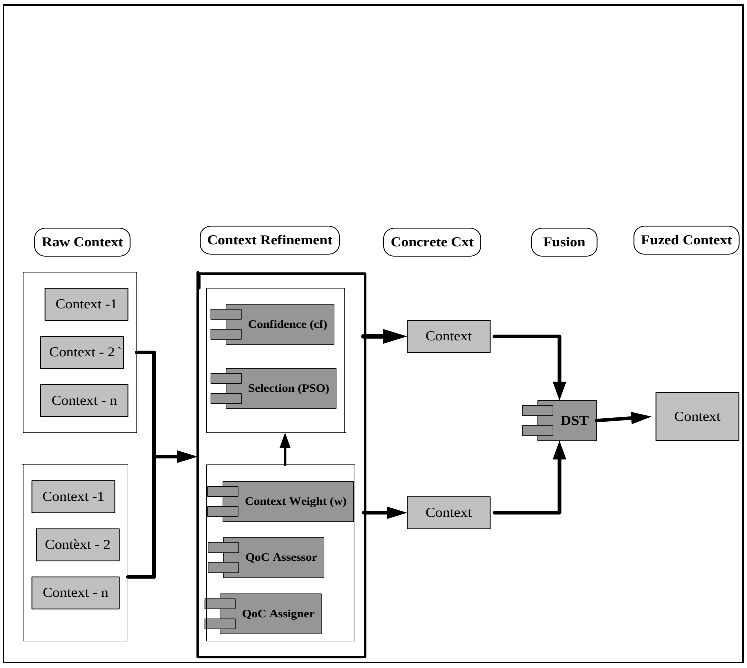

Figure 2. QoC PSO Context Refinement and Fusion Architecture

The context weight (w) component rates the raw context information on how close it is to the expected value. This rating is the weight that is assigned to every raw context. The QoC Assessor component uses the QoC parameters to calculate the QoC value for every context. The QoC Assigner assigns the obtained QoC value to raw contexts. In the selection phase, raw context with additional information from the previous phase is evaluated using combined confidence. The combined confidence component uses the context weight (w) and QoC assigned values to obtain confidence for each raw context. The selection (PSO) component uses this value to select the refined best value that can be used as context information. Table 1 summarizes the functionalities of the components in the proposed solution.

Table 1. Architecture Summary

No.	Component Name	Description
1	Context Information Sources (C(O))	IoT context objects, devices with sensory capabilities proving context information
2	Context Weighting (w)	Context information rating according the expected value
3	QoC Assessor	QoC assessor takes into account all QoC parameters to define the quality and retains a sign value between 0 and 1
4	QoC Assigner	QoC assignment component assigns all context sources the QoC value according to the Assessor
5	Combined Confidence (cf)	This component takes in the weight and QoC values to calculate the combined confidence
6	Context Selector (PSO)	Using the combined confidence PSO selects the most reliable context information
7	DST	Fuses selected most reliable context information to produce fused context.

4.4 Dempster Shafer Combination Rule

Dempster Shafer theory (DST) of evidence was first introduced in the context of statistical inference as a general framework for reasoning with uncertainty. This theory combines evidence from different sources and arrive at a degree of belief that uses all the acquired and available evidence. DST uses belief functions to ascertain the degree of belief for one question of probabilities. Used in fusion, the theory uses two aspects; one aspect deals with obtaining degree of belief for one question from subjective probabilities and the other combining degree of belief based on independent items of evidence.

In our work, we used the second aspect of the Dempster Shafer theory that deals with combining degrees of belief called the Combination Rule that is stated as follows;

$$m(C) = \frac{\sum_{A \cap B = C} m_1(A) m_2(B)}{1 - \sum_{A \cap B = \phi} m_1(A) m_2(B)}$$

(18)

Where m_1 and m_2 are mass functions for evidence A and B on C. This combination rule may give unexpected or unreasonable results because of the normalization effect that completely ignores conflict in its mass function.

Our method introduces the concept of combined confidence of the observed evidence by evaluating each value using the QoC and PSO in fusing evidence. QoC is used to calculate the combined confidence of observed evidences and PSO in selecting evidence with highest combined confidence. In the way conflict is taken into consideration and the combined results are more reliable. The following sections briefly describe how confidence is calculated and how context objects are selected.

Let $C(O)_{i,j}$ represent context objects that have collected context information about a real world entity as evidence and have been refined whose probability confidence map to mass function represented by $m'_1 C(O)_i \, and \, m'_2 C(O)_j$. Therefore to achieve context fusion using QoC for the best selected context objects using PSO, the new DST combination Rule will be as follows;

$$m'_1 \oplus m'_2 \left(CS(CO)_{i,j}\right) = \frac{\sum_{C(O)_i \cap C(O)_j = CS(O)_{i,j}} \partial\left(m'_1 C(O)_i m'_2 C(O)_j\right)}{1-\partial\left(\sum_{C(O)_i \cap C(O)_j = \phi} m'_1 C(O)_i m'_2 C(O)_j\right)} \quad (19)$$

Where ∂ is the combined confidence value used in the context selection criteria.

5. Discussion of Simulated Results

Our proposed method for context fusion yielded the following results as given in Table 2. Prior to fusion, context sensor data is refined to enhance its quality using combined confidence and PSO. The refinement process produces concrete context that is more reliable with minimum relative error. To evaluate its performance, our proposed method (DST/PSO) was compared to two other methods namely Dempster Shafer Theory (DST) and Weighted Sum of Products (WSP). All these methods were evaluated using a statistical method of standard deviation. The standard deviation was used to show the extent of the resultant merged values from the actual/expected standard deviation of the required sensor values.

We calculated the estimated relative errors of sensors given the reading $C(O)_{i,j}$ and the refined merged result $m'_1 \oplus m'_2 \left(CS(O)_{i,j}\right)$. The results are given in the confidence Table 2.

Table 2. Confidence Table for standard Deviations

	Context Objects		Methods			
No.	1	2	ACTUAL STD	DST	WSP	DST/PSO
1	0.235566483	0.105259997	0.288650938	0.242596540	0.094768205	0.290231463
2	0.039346481	0.194313527	0.290794149	0.242376184	0.094508479	0.285419316
3	0.458773609	0.431237350	0.292584708	0.244932143	0.095283443	0.286938121
4	0.354045422	0.495673109	0.288166247	0.245082803	0.121783327	0.289951046
5	0.678307215	0.048055955	0.290086275	0.244937115	0.142730670	0.288498113
6	0.343257728	0.719072366	0.289884838	0.239847932	0.159698211	0.284221043
7	0.980116989	0.542776697	0.284493941	0.236704786	0.173232304	0.284720528
8	0.545291466	0.215699421	0.280243767	0.234198043	0.184298059	0.281598814
9	0.278920795	0.920196714	0.281765595	0.232949917	0.193434895	0.281681497
10	0.235566483	0.105259997	0.279926899	0.229993161	0.201254880	0.275206552

The table has raw sensor data (context objects) to be fused and estimated relative error for the actual data, Dempster Shafer Theory, Weighted Sum of Products and our method PSO/DST. The Dempster Shafer method (DST) fuses raw context objects as independent items of evidence.

Taking context objects 1 and 2 from the table, the standard deviation for the three (3) methods were 0.242596540 for DST, 0.094768205 for WSP and 0.290231463 for our method. Compared to the standard deviation for the actual sensor values relative to the expected values, it can be observed that there is a strong correlation between the actual STD and DST/PSO. Our method's performance is far more superior to the compared methods as can be showed in figure 2. The graph show that the there is a minimum difference between actual STD and DST/PSO.

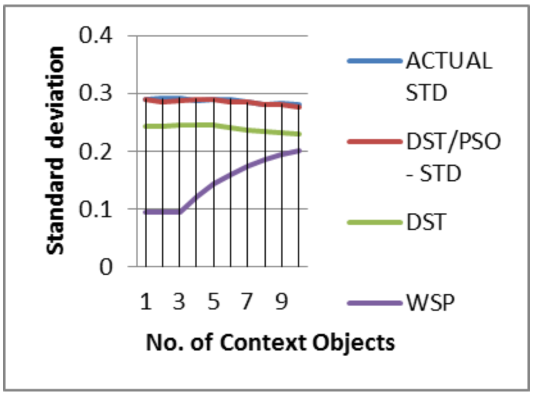

Figure 3. Behavioral Graph for the STD

Using the absolute difference between the actual and our method, it can be seen that the difference between the two values is leading to zero.

Table 3. Absolute Difference Values

	Context Objects		Methods		
No.	**1**	**2**	ACTUAL STD	DST/PSO - STD	**ABS DIF**
1	0.235566483	0.105259997	0.288650938	0.290231463	0.001580525
2	0.039346481	0.194313527	0.290794149	0.285419316	0.005374833
3	0.458773609	0.431237350	0.292584708	0.286938121	0.005646587
4	0.354045422	0.495673109	0.288166247	0.289951046	0.001784799
5	0.678307215	0.048055955	0.290086275	0.288498113	0.001588162
6	0.343257728	0.719072366	0.289884838	0.284221043	0.005663795
7	0.980116989	0.542776697	0.284493941	0.284720528	0.000226587
8	0.545291466	0.215699421	0.280243767	0.281598814	0.001355047
9	0.278920795	0.920196714	0.281765595	0.281681497	0.000084098
10	0.235566483	0.105259997	0.279926899	0.275206552	0.004720347

6. Conclusion and Future Work

Our paper highlighted context quality assessment and fusion in Internet of Things (IoT). The proposed method used quality of context (QoC) and Particle Swarm Optimization (PSO) to refine context. As part of the refinement process, context information was assessed by calculating its quality using QoC parameters and combined confidence. The process produced more reliable context information that were fused using the Dempster Shafer combination rule. The resultant fused information showed that combining context with high quality increases the credibility of the fusion process. Our research contributes to the rarely addressed notion of quality assessment in context information. In future we hope to use reasoning methods on refined context objects on a specific IoT domain.

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