

Context-aware QoI Computation in Multi-Sensor Systems

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Abstract

Multi-sensor systems are increasingly being deployed in many application scenarios due to the enormous potential they can offer. However, as the processing of sensory data often results in imprecise outcome, measuring the quality of information (QoI) in these systems has become an important issue. The measurement of QoI is usually performed by processing the elementary data provided by the heterogeneous sensors, which is also influenced by the techniques involved in sensor management. However, the effect of context, such as environmental geometry, sensor placement, orientation, time, and other parameters in computing QoI has not yet been explored extensively in the literature. This paper proposes a context evolution model and studies its impact in the QoI computation. In particular, we show that the dynamic context information can be utilized to manage a multi-sensor system to improve its QoI.

1. Introduction

Multi-sensor systems are increasingly being deployed in many application scenarios such as habitat monitoring, forest fire detection, surveillance, and activity detection for assisted living. These systems usually employ multiple heterogeneous sensors and process the multimodal data obtained from these sensors in order to identify higher level information of interest, such as the rise of forest temperature and the detection of an abandoned object. However, as the processing and fusion of sensory data often results in imprecise outcome [8], measuring the quality of information (QoI) in these systems has become an important issue.

The QoI in a sensor-based system may be defined as the degree of goodness of information that reflects the aspects of physical environment observed by the sensors [12]. Researchers have used several attributes to represent the QoI of such systems. For example, timeliness and confidence in [3]; certainty, accuracy, integrity and timeliness in [4].

Other attributes can also be considered as the QoI attributes depending on the requirements of the target application. The different QoI attributes are computed based on many factors. For example, the confidence is computed by considering the probability of correct detection; the integrity is obtained by determining whether the source data streams have been altered during transmission and so on.

While processing the various sensory media to obtain higher-level information and compute QoI, a sensor-based system inherently needs to leverage context information, such as lighting condition and sensor coverage. The context may be considered as accessory information that greatly influences the information acquisition process. For example, a video sensor becomes useless at night due to poor lighting condition and hence data from other appropriate sensors should be selected for processing and QoI computation. The example clarifies that context has an influence on how to manage the available sensing resources and fuse the observation to gather relevant information about the observed environment, which in turn effects the computation of QoI. In other words, the typical sensor management [2] may utilize the various context information to perform the overall surveillance or monitoring in an efficient manner.

However, existing sensor-based systems either ignore the explicit context influence or they consider context in a static manner. For example, authors in [11] have used the environment geometry and sensor location as a static context information in a multi-sensor surveillance scenario. These works and many others have not also considered the fact that context evolves over time. For example, the coverage area of a pan-tilt-zoom camera sensor changes over time which refers to the change of context information. Therefore, it is obvious that the effect of changing context in QoI remains to be unexplored to its full potential, which we aim to explore in this paper.

Our contribution in this paper is two-fold. First, we identify the different context parameters that influence sensor management tasks with respect to the selection of appropriate sensors and model the individual context parameters to

show their evolution over time. Second, we elaborate how the different parameters influence the QoI computation. The rest of the paper is organized as follows. In Section 2 we comment on some related literature. The proposed method is presented in Section 3 followed by the experimental results in Section 4. The conclusion along with possible future directions are presented in Section 5.

2. Related Work

We present some existing research on quality of information, context-awareness and sensor management in order to conceptualize the proposed work in this paper. The works reported in [3] and [4] address the QoI in sensor-based systems. The authors in [3] study the impact of sensor sampling on the confidence and timeliness attribute of QoI, while in [4] the authors provide a general model for determining QoI in terms of certainty, accuracy, timeliness and integrity. However, these works do not take context into consideration, such as lighting condition, in computing the QoI.

The PROCON infrastructure in [1] provides a distributed mechanism to collect context information from the sensor network environment. However, there is no indication of the use of sensor coverage, time and other context parameters in computing the quality of the observed information of interest. In [6], the authors provide a middleware with statistical QoI bounds and accordingly tries to adjust the number of activated sensors in a dynamic fashion, which may be considered as the management of sensor networks [2]. However, it does not provide any indication whether the different environment context would have any impact on the target QoI bounds. Unlike the above works, we illustrate the use of several context parameters and show how they influence the selection of appropriate sensing resources while computing QoI.

3. Proposed Model

Figure 1 shows a high-level view of the proposed model. Here the sensor management unit selects the appropriate sensing resources based on the external information as well as context determined by the fusion unit. The selected sensing devices send observation streams to the fusion center, which processes the input data and determines the high-level information through fusion and computes the QoI. The fusion center also uses the external context information. Besides computing QoI, it determines some context parameter, such as lighting condition when applicable, and sends this information to the sensor management unit, which in turn uses this information to select sensing resources. The goal of this setting is to improve the QoI by considering con-

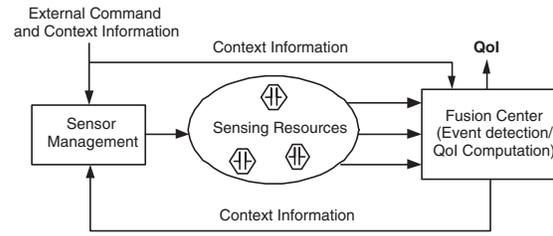


Figure 1. Schematic view of the proposed model

text to effectively manage the sensors in a multi-sensor system. To further explore the proposed model, we provide an overview of QoI attributes, the context model and the effect of context in QoI in the following section.

3.1. QoI Attributes

In our earlier work [4], we used four quality attributes to represent QoI of a multi-sensor system, which we briefly describe in the following.

3.1.1 Certainty.

This is a measure to reflect how certain the obtained evidences are. We compute the certainty of evidence in terms of event detection probability. There are various classification methods (e.g. Bayesian classifier) that are usually adopted to obtain such probability score. We adopted a Bayesian formulation to compute the value of *certainty* (q_1) for the information of interest as described in [5].

$$P_{i,k}^j = \frac{(P_i^j)^{f'_i} \cdot (P_k^j)^{f'_k} \cdot e^{\gamma_{i,k}^j}}{N} \quad (1)$$

where, the term N is a normalization factor to limit the probability value within $[0, 1]$. $P_{i,k}^j$ is the aggregate certainty value based on two sensors i and k . P_i^j and P_k^j are the observation scores with respect to information j based on i^{th} and k^{th} sensors, respectively. $\gamma_{i,k}^j \in [0, 1]$ refers to the agreement/disagreement factor between the two sensors which is computed based on their current observation score. f'_i and f'_k is the weight assigned to the i and k sensor for the j^{th} information of interest.

3.1.2 Accuracy/confidence.

Accuracy usually refers the ratio of the number of correctly detected events to the total number of events that occurred in the environment. However, it is only possible to obtain the number of correctly detected events through physical

investigation or by comparing the sensor observation with the reference knowledge. Therefore, we use the measure of confidence instead of accuracy and proposed a model to compute confidence dynamically [5] with the motivation that in dynamic sensor environment it is impractical to have the ground truth information before hand. Our model uses the differences in observations among the participating sensors and adopts a reward and punishment mechanism to evolve the *confidence* (q_2) of the individual sensor with respect to determining the higher level information of interest. This is precisely represented as,

$$\text{if } P_{\phi_1}^j \geq P_{\phi_2}^j$$

$$\begin{cases} f_{m \in \phi_1}^j(t) = \frac{1}{Z} \cdot f_m^j(t-1) \cdot e^{(\lambda \cdot \alpha)(t)} & (\text{reward}) \\ f_{n \in \phi_2}^j(t) = \frac{1}{Z} \cdot f_n^j(t-1) \cdot e^{-(\lambda \cdot \alpha)(t)} & (\text{punishment}) \end{cases} \quad (2)$$

else

$$\begin{cases} f_{n \in \phi_2}^j(t) = \frac{1}{Z} \cdot f_n^j(t-1) \cdot e^{(\lambda \cdot \alpha)(t)} & (\text{reward}) \\ f_{m \in \phi_1}^j(t) = \frac{1}{Z} \cdot f_m^j(t-1) \cdot e^{-(\lambda \cdot \alpha)(t)} & (\text{punishment}) \end{cases}$$

Where f_m^j and f_n^j refers to the updated confidence of the sensors in group ϕ_1 or ϕ_2 , respectively. The group ϕ_1 and ϕ_2 are the two groups of sensors, one supporting an evidence while the other opposing an evidence. $\lambda = \text{abs}(P_{\phi_1}^j - P_{\phi_2}^j)$ shows the difference of opinions and is used as a reward/punishment factor. α is a growth/decay factor for reward and punishment. $P_{\phi_1}^j$ and $P_{\phi_2}^j$ refers to aggregate probability score for the two groups. Z is a normalization factor.

3.1.3 Timeliness

The timeliness is a measure to determine whether the information about the occurrence of an event is available at the desired time. For example, if there is a fire in the forest, the system should be capable of reporting that event within the desired time delay. We model the *timeliness* (q_3) attribute using the following general equation [4].

$$q_{3,j}(t) = T_j / (T_j + \Delta) \quad (3)$$

Where, T_j is the desired time to identify a high-level information. Δ is the extra time taken by the system.

3.1.4 Integrity

The *integrity* (q_4) quality attribute is used to determine whether the source data or processed information has been manipulated in transition through unauthorized means. We adopted a watermarking scheme to first embed watermark with the source data provided by the sensor and later extract the watermark at the destination center to verify whether the source data has been altered during transmission. A general formalism for integrity [4] can be provided as,

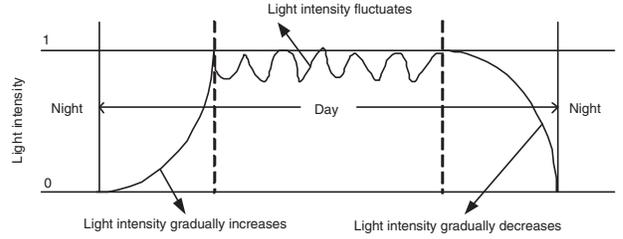


Figure 2. Evolution of lighting condition

$$q_{4,j}(t) = \text{Dist}(W_S^j, W_D^j)(t) \quad (4)$$

Where, *Dist* is a function for computing the cosine distance between the source authentication data W_S^j and the extracted authentication data W_D^j with respect to the the j^{th} information, respectively.

3.2. Context Evolution

There are several pieces of context information such as lighting condition, sensor coverage and time, which have an influence on QoI. This is elaborated in the following. In the text, we also show that the context transition from one context situation to another may be smooth or abrupt. For example, the change of lighting condition from day to night may result in a smooth context transition, while an abrupt context transition may refer to the change of time when the system has to perform certain task. In the following we model the evolution of context.

3.2.1 Lighting Condition

The environmental lighting condition is one of the fundamental context parameters that greatly influences the QoI condition. For example, depending on the light intensity and changes of illumination, data from a selected set of sensors may be considered for obtaining the information of interest. The lighting condition changes over night and day. In Figure 2, we show the evolution of this change.

Figure 2 shows that the lighting condition changes gradually from night to day and day to night, which follows an exponential pattern as stated in [9], while it fluctuates randomly during the day time. Context determination for the change of lighting condition can be done by analysing the quality of image captured by camera sensor. Several existing techniques can be used for image quality estimation.

3.2.2 Sensor Location and Coverage

Sensor location and coverage is an important context information. However, determining the location and coverage is

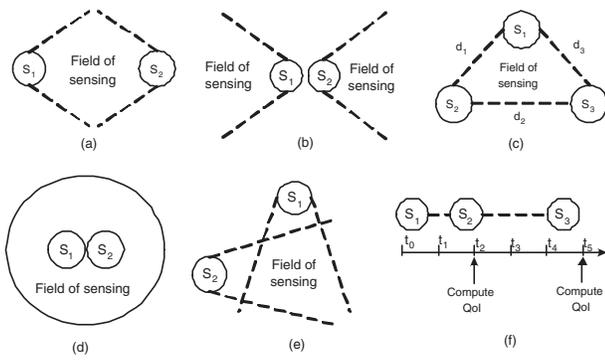


Figure 3. Spatial and temporal context

a challenging task [7]. In a multi-sensor system, different types of sensors have different coverage limits. However, these limits cannot be pre-determined due to the changes of sensor's field of view. For example, the coverage of a pan-tilt camera changes constantly, which have an impact on the value of QoI attributes. Sensor coverage can broadly be classified as spatial coverage and temporal coverage. Spatial coverage refers to similar, different or overlapping area of sensing among a set of sensors. Temporal coverage refers to the spatial coverage over a period of time. Figure 3 shows different example coverage scenarios, which we describe in the following:

1) *Spatial coverage*: We classify the spatial coverage into three sub-groups that are, exactly same area of coverage (sub-group1), exactly different area of coverage (sub-group2) and overlapping area of coverage (sub-group3). Figure 3 (a), (c), (d) refers to sub-group1, Figure 3 (b) refers to sub-group2 while Figure 3 (e) refers to sub-group3.

In sub-group1, Figure 3(a) shows that two sensors are placed in a way to cover the same observation area. In such cases the occurrence of an event can be captured by both the sensors. For example, the media streams obtained from two cameras facing each other can be processed at the same time for finding blobs to detect the presence of a person in the monitored environment. Similarly, Figure 3(c) shows that three sensors have the same field of sensing and hence the detection of an event may be determined by combining their observations. The distance among these sensors may also be considered to determine whether they are neighbours and whether their observations should be aggregated for determining the occurrence of an event. However, this will also depend on the type of sensors and the information item we are interested in. In Figure 3(d), the two sensors have a 360° field of sensing. Therefore, their observations can be considered at a certain time. For instance, two audio sensors are placed in such a manner. Obviously the detection of some information item (e.g. a person is shouting) can be based on the outcome of these sensors.

In sub-group2, Figure 3(b) depicts that the two sensors have exactly the different field of sensing. Therefore, the observation from S_1 may not be combined at an instance with the observation of S_2 as they will provide contradictory information. In sub-group3, Figure 3(e) shows that the two sensors have some overlapping field of sensing. Therefore, any events occurring in that overlapping region may be decided based on the observations of both sensors. However, the determination of events in the overlapping region is not always obvious from the sensory stream.

2) *Temporal coverage*: Temporal coverage is the case when two or more sensor observation may be combined over a timeline. Consider for example, Figure 3(b) and Figure 3(f). Although in Figure 3(b) the sensors have different field of sensing, an object moving from the S_1 's field of sensing to S_2 's field of sensing can be determined by combining the observations of both the sensors over a period. Similarly, in Figure 3(f) we show that the observations of the different sensors can be computed over a timeline. For example, at time t_2 the observation of sensors S_1 and S_2 can be combined together, while at time t_5 the observation of the sensor S_3 can be combined with the group of sensors S_1, S_2 .

In order to address the sensor location and coverage issue, existing research have used several enabling technologies. For example, use of GPS for location determination. The coverage issue, especially the spatial coverage, is addressed in [7] by using the techniques of computational geometry and graph theory.

3.2.3 Time

Time is the basic context information that can effect the QoI computation in many ways. For example, during the day or night, a multi-sensor system may be put into alert situation in some specified period of time. Based on a time context, a system might be computing QoI in frequent interval than other time due to some prior observations and settings that would have an impact on QoI.

3.3. Context Influence on QoI

In this paper, we show the context influence from the sensor management perspective, that is, by selecting the appropriate sensors based on the change of context. This is done by dynamically adjusting the weights of the sensors. In order to show the influence of context in QoI, we follow a two-level approach, a) analyze individual context influence on QoI and b) analyze overall context influence on QoI.

3.3.1 Influence of Lighting Condition on QoI

Based on the varying lighting conditions, we adjust the weights of the different types of sensors. As depicted in

Figure 2, the lighting condition gradually reduces in an exponential pattern from a transition between day and night. Therefore, the weights of the sensors whose observation is affected by such context change, such as camera sensor, should be decayed accordingly. On the other hand, the weights of the sensors whose observations do not suffer from changing lighting condition should be adjusted. For example, the weights of the audio and RF-based motion sensors would have similar or higher weight in such situation.

3.3.2 Influence of Sensor Coverage on QoI

In order to show the impact of sensor coverage on QoI, we define some high-level rules. Based on these rules, a multi-sensor system can dynamically determine which sensor observation to use and fuse in a particular observation area. Example of some rules are given in Table 1.

3.3.3 Influence of Time on QoI

Similar to the coverage context, the influence of time on the computation of QoI may be shown by defining some simple rules as presented in the bottom half of Table 1. Time context based rules are mostly defined based on prior knowledge. For example, in traffic monitoring scenario the sensors in strategic locations may be activated during the morning and afternoon rush hour, which can be defined by specific rules.

3.3.4 Influence of Overall Context on QoI

As the context consists of multi-dimensional information, such as lighting condition (L), sensor coverage (C) and time (T), the influence of one particular type of contextual information can not be only considered as an influence for the context as a whole. To explain this, let us consider the context as a tuple $C_x = \langle L, C, T \rangle$, with two different sets of values as $C_x^1 = \langle L_1, C_1, T_1 \rangle$ and $C_x^2 = \langle L_2, C_2, T_2 \rangle$. Therefore, the effect of C_x^1 as a whole would not be the same as that of the individual context parameters L_1 , C_1 or T_1 . In the same way, the effect of C_x^1 and C_x^2 on QoI would be different. Several strategies can be adopted to address this issue. One way would be to prioritize the individual context parameter and perform a combination. Another way would be to find out if there is any conflicting weight assignment. Yet another way would be to define some aggregation rules for the overall context effect on QoI. In this paper we adopt the latter strategy for simplicity.

4. Experimental Results

We performed preliminary experiment to demonstrate the effect of context evolution in QoI computation. For our

Table 1. Some rules based on coverage area

Context-rules (coverage related)	Description of coverage based rules
$Cov_j(S_i, S_m) = 1$	Common coverage between sensors S_i, S_m . The fused observations impacts QoI.
$Cov_j(S_i, S_m) = 0$	No common coverage between sensors S_i and S_m . Sensor observations are not fused.
$0 < Cov_j(S_i, S_m) < 1$	Partial coverage. Observations will be fused only if the event occurs in overlapping area.
Context-rules(time related)	Description of time based rules
$t_3 < t < t_6$	Example: activate all sensors in zone A

experiment, we used simulated data for three camera sensors and two audio sensors. We assume these sensors are deployed in an observation area to cover a particular region of interest. Recall, we use four quality attributes for representing QoI. Therefore, our objective of this experiment is to analyze the effect of context on these four attributes. For this we first consider the certainty (q_1) as the quality attribute and lighting condition as the context parameter. In real scenario, the certainty value might be obtained as a score representing the probability of detection based on the individual sensor and the lighting condition might be determined by applying image quality estimation techniques.

In our simulated data, we consider at a particular instance the certainty, $q_1 \in [0, 1]$, value for the five sensors as 0.65, 0.70, 0.58, 0.65, and 0.71 and the average image quality values based on the three camera sensors are 0.70, 0.80 and 0.55. Now, if we only consider the initial sensor weight (pre-computed confidence) without taking into consideration the context parameter (image quality scores), we obtain an overall certainty score using eq. (2), which is 0.72 for example. We also compute the overall certainty score by considering the context information. For this, we first readjust the weights of the sensors by taking the image quality estimates. Note that, a decay in lighting condition would reduce the weight in camera sensors and at the same time increase the weights of the audio sensors. Now based on these new readjusted weights, we determine which of the sensor observations to consider for QoI computation. This is done by only considering those sensors whose readjusted weights fall within a threshold.

In our QoI model, the second QoI attribute is the confidence (q_2) attribute, which is computed based on the overall certainty score. Therefore, the effect of lighting context in the case of confidence can be shown the same way as explained for the certainty score. The third QoI attribute is the timeliness (q_3) for which we provide analytical argument. For example, the incorporation of context change allows us to dynamically select the sensors for information processing and the number of sensors in that case would be less than when using static or no-context information. Therefore, the timeliness value will increase provided that fewer number of sensor data need to be processed. Similarly, for the case

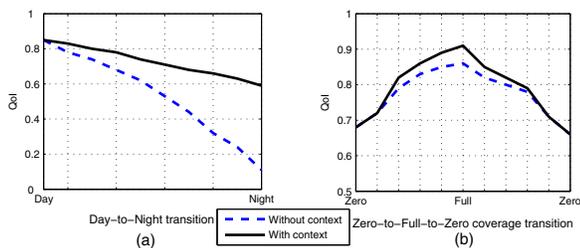


Figure 4. Context effect on QoI

of integrity (q_4) quality attribute we have to verify the data from fewer number of sensors, which will also reduce the chance of tampering in the data.

Like the lighting condition context, we can also analyze the effect of sensor coverage context in QoI computation. For this we have to first determine the sensor coverage given the deployed sensor in the environment. The work in [7] is a handy reference for analysing the spatial context for general sensor network while the work in [10] may be consulted for multimedia sensor domain which has different coverage settings. Once the coverage is determined, we can dynamically readjust the weights of the sensors and study the impact of this context information in QoI computation. Finally the effect of time can also be demonstrated based on the defined rules. Due to space limitations, we skip the detailed experimental analysis. However, in Figure 4 we graphically show the trend of the impact of context into the QoI computation mechanism. In Figure 4(a), we show the impact of audio and camera sensors during the transition from day to night. It shows that the overall QoI gradually reduces towards night as the system has to only depend on the audio sensors for decision making (in this case). However, if context is taken into consideration, the QoI would be higher than the case when context is not considered due to the fact that the context change can be used to readjust the weight of the sensors and the selection of the sensors can be done more intelligently.

Figure 4(b) shows the case of sensor coverage for camera sensors. It depicts that a better QoI can be obtained when the sensor coverage is considered. Clearly based on the coverage, the observation from a set of sensors will be ignored, which will reduce the influence of uncorrelated data from the QoI computation process. While at the same time, the observations of the sensors will be fused together given they have some overlapping or common coverage.

5. Conclusion

In this paper we presented an approach to analyze the effect of context information such as lighting condition, sen-

sor coverage, and time in computing QoI. We showed that the evolution of context may be utilized to dynamically adjust the weights of the sensors that facilitates selecting the right set of sensors given the dynamic context change. We used simulated data to demonstrate the suitability of the proposed approach. In the future, we wish to conduct extensive real-life experiment to further explore this proposal.

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