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Learning Multi-Sensor Confidence using Difference of Opinions

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Abstract – *Multiple sensors are being employed in different environments for performing various observation tasks and detecting events of interest occurring in the environment. However, all the sensors deployed in the environment do not have the same confidence level due to their differences in capabilities and imprecision in sensing. The confidence in a sensor represents the level of accuracy that it provides in accomplishing a task, which can be computed by comparing the current observation of the sensor through tedious physical investigation. Confidence computed in this manner is static and does not evolve over time. Moreover, performing physical investigation for checking the accuracy of the sensor observation is not feasible in a running system due to the overhead in incurs. Nevertheless, it is essential to know how the sensors are performing in a real-time scenario. This paper addresses this issue and proposes a novel method to dynamically compute the confidence in sensors by learning the differences of their individual opinions with respect to the particular detection task. Experimental results show the suitability of using the dynamically computed confidence as an alternative to the accuracy measures of the sensors.*

Keywords – *Sensor confidence, media streams, event detection, opinions.*

I. INTRODUCTION

Sensors of similar or different modalities are being used in different observation scenarios, such as monitoring the activities of elderly people in an ambient-assisted environment; detecting the unusual events in a surveillance premise; observing a critical infrastructure; and so on. The core motivation of using multiple sensors is to obtain a better perception of the observation environment and the activities happening in the environment. Usually different sensors have different confidence levels in performing various observation tasks [1]. For example, a video stream may have higher confidence than an audio stream in identifying a person. Therefore, an observation task may be better performed by appropriately taking into consideration the different confidence levels of the sensors.

Several researchers [2], [3], [4], [5] have used confidence measure as a representation of accuracy in different application contexts. For measuring the accuracy, it is required to physically investigate the current evidences provided by a sensor. However, this approach may not be adopted in a real-time scenario as it involves excessive manual intervention. Also, confidence measured in this manner remains static and does not evolve over time. The statically computed confidence does not convey the true status of the sensors for the evidences they provide in the real-time instances. In a practical environment, the confidence in a particular sensor may increase or decrease over a period of time depending upon its observation accuracy, thereby requiring a mechanism to compute confidence dynamically. The addition of sensors to the existing sensor arrays in a running system also poses the challenge on how to determine the confidence of the newly added sensors. In this paper we address this issue of dynamic computation of confidences in sensors.

Confidence has been previously used in sensor data processing. In [2], the authors used the Dempster-Shafer theory to compute the overall confidence of a group of sensors and use that confidence while fusing data. The authors used the past accuracy of the sensors to compute the confidence but did not address the evolution of such confidence over time. The work in [6] and [1] proposed a dynamic method to compute the confidence of individual sensors. The model presented in [6] considers the performance of individual sensors over a period of time compared to other sensors to compute the confidence of each sensor. Although, their method dynamically measured the confidence in each sensor, it is not clear how they measure the similarity of performance among sensors. A different approach has been adopted in [1] where the authors initially consider a set of trusted media streams to compute the confidence of other non-trusted streams. They used the agreement/disagreement among the trusted and non-trusted media streams and based on this association, compute the evolving confidence of the non-trusted streams using a Bayesian formulation, while the confidence of the already trusted streams remains static.

Unlike the above works, we propose a novel method that utilizes the difference of opinions measured from the sensor observation. Our work is consistent in motivation with [6] and [1] in that they also provide a mechanism to derive the confidence of sensors dynamically. However, the proposed method does not assume a predetermined set of trusted sensors unlike [1], due to the fact that such a set of trusted sensors may start behaving unreliably and provide bogus data over the period of time. Therefore, the confidence in the sensors should be learned and evaluated dynamically, which is the focus of this paper.

Our contribution in this paper is two-fold. First, we provide a mechanism to dynamically compute the confidence in sensors. Our approach determines the difference of opinions resulted from the observations of the sensors, and uses this difference to either increase or decrease their confidence as analogous to the reward and punishment mechanism. Second, we experimentally show that the confidence computed using the proposed method is comparable to the manual approach of determining accuracy, thereby showing the suitability that the dynamically computed confidence can be a viable alternative to the measure of accuracy.

II. PROPOSED MODEL

A. Overview

The proposed method computes the confidence of the sensors based on their observation of events. The confidence in a sensor represents the level of accuracy that it provides in accomplishing a task (detecting an event). Therefore, confidence in a sensor would be different for different detection tasks. We denote the confidence in a sensor corresponding to the detection of j^{th} event as f_i^j, where $i = 1, 2, \ldots, n$ and n is the number of sensors. In the following, we provide the highlight of our proposed method that is used to compute f_i^j on the fly.

- In our model, the current observations of the sensors are obtained in probability scores based on the processing of the sensory media streams. This involves the use of classification strategies (e.g. SVM, Bayesian) in classifying a particular observation task or event. The score obtained in this manner is considered as the opinion of the invidual sensor, which we will use in deriving the confidence computation model.

- The proposed method uses the past accuracy of the sensors as their initial confidence, which is considered as a static measure of confidence. This can be experimentally computed by comparing the outcome of the online sensor observation with the ground truth and by repeating the process multiple times to obtain a steady value. The process of measuring the initial value of confidence is presented in Section B.

- The confidence of a sensor may increase or decrease over time and hence the static confidence does not represent the true accuracy level of the sensor in a running system. To model the evolution of confidence, we adopt the principle of reward and punishment. We take the opinions of the sensors involved in performing a common observation task and group the opinions into two subgroups, one supporting the occurrence of the particular event and the other opposing the occurrence. We then determine the winning group and increase the confidence of the sensors in that group, while at the same time we decrease the confidence of the sensors of the other group by a factor. The determination of the winning group is based on the combined probability scores that represents the group opinion. This process is explained in Section C.

B. Static Confidence

The static confidence is computed from the past accuracy of each of the sensors. The past accuracy of the sensors is determined by comparing the observations provided by the sensor with the ground truth in the training session. The measure of the past accuracy of the sensors may be represented using four possible parameters including true positive (TP), false positive (FP), false negative (FN) and true negative (TN). For a sensor i, these parameters are used to compute the accuracy of the evidences for the occurrence of event j as, $Acc_i^j = \frac{TP_j + TN_j}{TP_j + FP_j + FN_j + TN_j}, 1 \leq i \leq n$. Acc_i^j is an average value obtained through multiple training iterations. At the early state of deployment, the past accuracy of the sensor observation will be assigned as the value of initial confidence, i.e. $f_i^j(0) = Acc_i^j, i = 1, 2, \ldots, n.$

The initial confidence or the past accuracy of the sensors as presented are learned based on their individual observations. However, whenever a new sensor is added to an environment, it may be difficult to obtain the past accuracy of that sensor, as it will be influenced by the current settings and environmental context. In such cases, the system designer may assign the initial confidence as 0.50 or as is specified in the sensor's technical specification, which will be later evolved over time using the proposed method of determining dynamic confidence. The evolution of sensor confidence is described in the next section.

C. Dynamic Confidence

Let an environment use the set $\mathbb{S}_n = \{S_1, S_2, \ldots, S_n\}$ of $n \geq 2$ number of sensors for monitoring the events occurring in the environment. For a particular event, let n' number of co-related sensors be used to obtain the decision for a common observation task. Among these n' sensors, let there be two groups of sensors, ϕ_1 and ϕ_2, where ϕ_1 is in support of the evidence and ϕ_2 is not in support of the evidence. To illustrate this grouping, let us consider the observation scores of two sensors as .85 and .40. Now considering a threshold of .50, the two scores can be put in two groups. Therefore, the score .85 will be in the group ϕ_1 supporting the occurrence of an event, while the score .60 $(= 1 - .40)$ will be in the group ϕ_2 supporting the non-occurrence of that event. In a similar fashion, the observation scores of the sensors performing a common observation task are divided into the two groups. We utilize the different of the observation of the two groups to evolve the confidence of the sensors belonging to these groups.

To leverage the difference of opinions, we first aggregate the probabilities of the groups ϕ_1 and ϕ_2. By adapting the mechanism used in [7], we compute the overall probability of the evidences supporting the occurrence for an event $I_j, 1 \leq j \leq r$ (r being the total number of events) as follows:

The probabilities of the evidences provided by any two sensors S_i and S_k can be fused together by using a Bayesian approach as,

$$P^j_{i,k} = \frac{(P^j_i)^{f'_i}.(P^j_k)^{f'_k}.e^{\gamma^j_{i,k}}}{N} \quad (1)$$

where, the term N is a normalization factor to limit the probability value within $[0, 1]$, which is expressed as,

$$N = (P^j_i)^{f'_i}.(P^j_k)^{f'_k}.e^{\gamma^j_{i,k}} + (1 - P^j_i)^{f'_i}.(1 - P^j_k)^{f'_k}.e^{-\gamma^j_{i,k}} \quad (2)$$

In eq. (1) and (2), P^j_i and P^j_k are the probability of the sensors S_i and S_k, respectively. The term $f'_i = f_i/(f_i + f_k)$ and $f'_k = f_k/(f_k + f_i)$ are the two factors computed from the past confidence of sensors S_i and S_k at time $t - 1$, where $f'_i + f'_k = 1$. Also, f'_i and f'_k represents the weights assigned to the sensor observations based on their changing confidence. Note that, while combining the probabilities of evidences between a group and a single sensor, we will require obtaining the group confidences, which will be calculated by averaging the individual confidences of the sensors in the group. We will shortly show how the confidences of sensors are obtained at time t. The term $\gamma^j_{i,k} \in [-1, 1]$ refers to the agreement coefficient between the sensors S_i and S_k. This is used as a growth factor for fusing the probability. The value -1 indicates a full-disagreement, while 1 indicates a full-agreement among the media streams provided by the sensors. The value of $\gamma^j_{i,k}$ at time t between any two sensors (for n sensors, there would be n_{C_2} combination) can be computed by combining their current agreement/disagreement with their past value as,

$$\gamma^j_{i,k} = \beta[1 - 2 \times |P^j_i(t) - P^j_k(t)|] + (1 - \beta)[\gamma^j_{i,k}(t - 1)] \quad (3)$$

In eq. (3), the term $\gamma^j_{i,k}(t-1)$ represents the past agreement between the sensors S_i and S_k. The term $1 - 2 \times |P^j_i(t) - P^j_k(t)|$ represents their current agreement value. The weighting factors β and $1 - \beta$ are assigned to the current and past agreement coefficient, respectively. While computing the agreement coefficient between a group of sensors and a single sensor, the pairwise value of the agreement coefficient is averaged using average-link clustering [8]. For example, the agreement coefficient between a group (S_i, S_k) and a single sensor S_m is computed as $\gamma^j_{i,k,m} = (\gamma^j_{i,m} + \gamma^j_{k,m})/2$.

Finally, eq. (1) is iteratively executed to combine the observation scores of all the sensors in group ϕ_1 to obtain the aggregate probability $P^j_{\phi_1}$. In a similar fashion the aggregate probabilities of the evidences supporting the non-occurrences of an event is computed, which is $P^j_{\phi_2}$.

Using the above formulation, we now have $P^j_{\phi_1}$ and $P^j_{\phi_2}$ for the two groups of sensors. If $P^j_{\phi_1} \geq P^j_{\phi_2}$, the final winning decision from the sensors would be the one provided by the group ϕ_1. Otherwise, the system will assume that the particular event did not occur with a probability of $P^j_{\phi_2}$. Therefore, intuitively we can adopt a reward and punishment mechanism and increase the confidence of the sensors in group ϕ_1 when $P^j_{\phi_1} \geq P^j_{\phi_2}$, and at the same time decrease the confidence of the streams in group ϕ_2, and vice versa. Hence, we model the dynamic confidence in each of the sensors as,

$$f^j_{kk \in \phi_1}(t) = \begin{cases} \frac{1}{Z}.f^j_{kk}(t-1).e^{(\lambda.\alpha)(t)}, \textbf{if } P^j_{\phi_1} \geq P^j_{\phi_2} \\ \frac{1}{Z}.f^j_{kk}(t-1).e^{-(\lambda.\alpha)(t)}, \textbf{otherwise} \end{cases} \quad (4)$$

$$f^j_{kk' \in \phi_2}(t) = \begin{cases} \frac{1}{Z}.f^j_{kk'}(t-1).e^{(\lambda.\alpha)(t)}, \textbf{if } P^j_{\phi_2} > P^j_{\phi_1} \\ \frac{1}{Z}.f^j_{kk'}(t-1).e^{-(\lambda.\alpha)(t)}, \textbf{otherwise} \end{cases} \quad (5)$$

where, the terms $f^j_{kk}(t - 1)$ and $f^j_{kk'}(t - 1)$ are the evolving confidence of each of the sensors in group ϕ_1 and ϕ_2, respectively, with respect to the event I_j based on the individual sensor stream. Please note, for confidence evolution we have used an exponential model of growth, although other models may also be explored. The exponential terms $e^{(\lambda.\alpha)}$ and $e^{-(\lambda.\alpha)}$ are the growth and decay factors, respectively, based on current observations. The growth factor is used to positively evolve the confidence of the streams that are in support of the overall decision, i.e. when $P^j_{\phi_1} \geq P^j_{\phi_2}$. On the contrary, the decay factor is used to negatively evolve the confidence of the streams that are not in support of the overall decision, i.e. when $P^j_{\phi_2} \geq P^j_{\phi_1}$. The value of $\lambda = abs(P^j_{\phi_1} - P^j_{\phi_2})$. Also, α is the number that is used to control the rate of growth or decay in confidence and is experimentally determined. The term Z is the normalization factor to keep the value of confidence in $[0, 1]$. For an equation of the form $f.e^x$, the normalization factor can be determined as, $f.e^x + (1 - f).e^{-x}$. Similarly, we determine the normalization factor Z in eq. (4) and (5).

Given, i number of sensors are used in obtaining a decision, the overall confidence of the system in performing the j^{th} observation task may be computed by simply averaging the individual confidence values of the participating sensors as $f^j_{sys}(t) = \frac{1}{i}\sum^i_{mm=1} f^j_{mm}(t)$.

III. EXPERIMENTAL RESULTS

In order to demonstrate the effectiveness of the proposed method, we present the preliminary experimental result in a lab environment. In the following sections we describe the whole process.

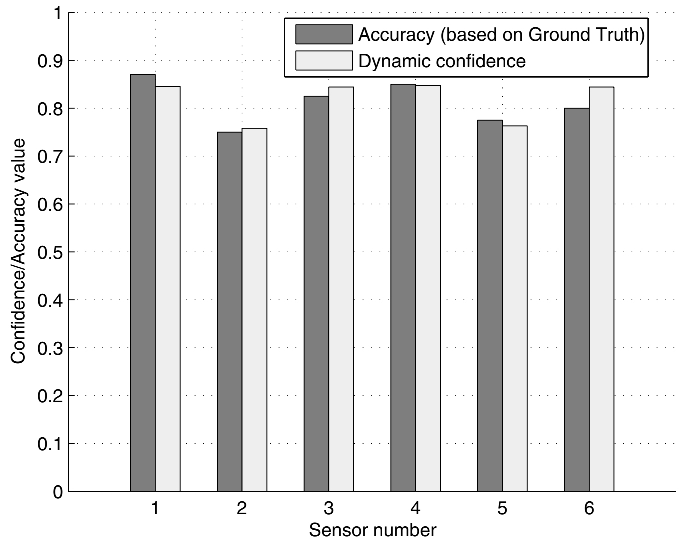

Fig. 1. Comparison between the static confidence/accuracy based on the Ground Truth and the dynamic confidence computed using the proposed method.

A. Environment Setup

In an experimental lab setting, we installed 6 temperature sensors. We control the temperature and record the current setting of the temperature as the Ground Truth. The sensors sense the temperature and based on that, the normal and abnormal temperature conditions are determined by the system. To do this, the actual temperature readings from the sensors are modeled using a Gaussian distribution and the mean and variance of the normal and abnormal temperature conditions are learned empirically.

To evaluate our proposed method, we recorded 50 observations from the six sensors over a period of 12 hours. Each observation from a sensor is classified into a normal or abnormal temperature condition using a Bayesian classifier, which provides a probability score corresponding to normal or abnormal temperature conditions.

B. Initial Accuracy Computation

First we manually compute the past accuracy of the sensors, Acc_i^j for $i = 1, 2, \ldots, 6$ as described in Section B. We use the data of the first 10 observations out of 50 and compare the results against the ground truth. This way, we compute the value of the past accuracy of the sensors and assign them as their initial confidence. Hence, for sensors $S_1, S_2, S_3, S_4, S_5, S_6$ we obtain the initial confidence as $f_1^j = 0.80, f_2^j = 0.70, f_3^j = 0.80, f_4^j = 0.80, f_5^j = 0.70, f_6^j = 0.80$. In the next section we describe the dynamic computation of the confidence.

C. Dynamic Confidence Computation

From the 50 sample observations we remove the data of the first ten observations as these are already used in computing the past accuracy of the sensors. On the remaining 40 sample observations, we apply our method by taking the data of one observation (for all the six sensors) in one iteration and update the current confidence values of each of the sensors using eq. (4) and (5). We empirically determine the value of $\alpha = 0.015$ to use in eq. (4) and (5), which controls the rate of growth/decay of the confidence values. We then manually compute the accuracy of the sensors based on these 40 observations using the formulation described in section B and make an average with the previously computed accuracy from the first 10 observations. This gives us the manually computed accuracy value for all the sensors. Our objective is to show that the manually computed accuracy value is comparable to the confidence values that are dynamically determined using the proposed method. In Figure 1, we plot and compare the manually computed accuracy to the dynamically computed confidence for all six sensors.

D. Discussions

In our preliminary experiment, we used six temperature sensors to monitor the environment for temperature changes. The event in our case is the monitoring of the temperature. However, other types of sensors could be used to detect different types of events, such as a video camera sensor can be used to detect a person, to identify a person and to find the blobs in an image sequence. Nevertheless, our method can be equally applied to different scenarios when different types of sensors are also used. From the conducted experiment, we obtained encouraging results as we have shown that the confidence computed using the proposed method is comparable to the one manually computed based on ground truth. For example, in Fig. 1, the manually computed accuracy of S_1, S_2 and S_3 is 0.875, 0.75 and 0.85, respectively. This values are close to the confidence values computed on the fly, which is 0.845, 0.757 and 0.847 for sensors S_1, S_2 and S_3, respectively. Similarly, the trend is shown for other sensors as well.

IV. CONCLUSION

This paper presents a novel method to dynamically compute the confidence of multiple sensors deployed in a observation environment. Our method learns the difference of opinions provided by a group of sensors while performing a certain observation task, and utilizes this difference to derive a reward and punishment based mechanism to dynamically compute their confidence. The dynamic computation of confidence eliminates the burden of the tedious process of statically determining the accuracy of the sensors, thereby providing the means to know the dynamic accuracy levels of the sensors used in a particular multi-sensor environment. Preliminary experiment shows the potential of the proposed method. We aim to perform large-scale experiments in the future and apply the proposed method in different realistic scenarios.

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