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A Consensus-Aware Pervasive Computing Systems Model for Smart Space Environments

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ABSTRACT

In this paper, we introduce some vital concepts related to the field of pervasive computing systems. We specifically introduce a new paradigm, "consensus-awareness" to the fold of this very important field of computing leveraging on the existing ideas of group theory and co-processing. We then apply rules of bio-engineered sparse connectivity integrating this new concept in a consensus mining algorithm. Simulation experiments are performed using the concept of group sensing with random number generators of a hypothetical temperature conditioning experiment. The results of simulation experiments have proved the efficacy of the proposed approach in deciphering novel patterns from uncertain random data.

Keywords: Bioengineered processing, consensus awareness, consensus mining, group theory, smart campus.

1. INTRODUCTION

Smart campus, a term referring to a delimited physical area composed of several buildings and where a variety of Internet of Things (IoT) sensors and/or actuators within the buildings and monitor the physical environment (Borgia et al., 2018) has become a very important research topic in recent times. Several research studies of smart campuses have evolved some of which include the investigation of the efficacy of smart classrooms for improving learning experiences (MacLeod et al., 2018), enhancing user comfort via smart conditioning using a majority voting scheme (Carreira et al., 2018), enhancing the experiences of wheel chair users via smart transport (Barbosa et al., 2018). From this limited examples, it is obvious that the Smart Campus plays an important role in improving the experiences and operations of students and workers in our university campuses, colleges, schools and other similar campuses. More recently, an important function and problem that has been identified in smart campus environment is how to aggregate user experiences. This has been identified as a group search problem and has been applied in different contexts (Chen et al., 2009; Schenato et al., 2011; Braca et al., 2008).

In this paper, we suggest a consensus-aware approach that seeks to reduce if not eliminate the bias associated with conventional machine learning decision making smart campus systems. Consensus based solutions are not a relatively new area of research as there have been a variety of applications such as in machine learning distributed solutions (Forero et al., 2010), in cooperative distributed sensing trust-aware consensus mining schemes against malicious ISSDF attacks (Vosoughi et al., 2016) and image description evaluation based consensus protocols as in (Vedantam et al., 2015).

However, the concept of 'consensus-aware' smart campus solutions is unknown in the smart campus literature and not popular in the smart space research community. The first use of the phrase "consensus-aware" appeared in (Rathore et al., 2016) where it was used to build trust among wireless sensor nodes (WSN); their proposed approach utilized a Laplacian matrix socio-psychological model leveraging on both spatial and temporal information in data obtained from the WSNs. Specifically, trust in the socio-psychological consensus aware context proposed in (Rathore et al., 2016) integrates three main components: Ability, Benevolence and Integrity. These components were combined to form a useful model of trust in the consensus-aware sense.

In our proposed solution, consensus awareness represents a mechanism for combining aggregated experiences from two or more smart space participants (or users) in a smart space environment. Our consensus-aware technique primarily employs End-Users (EU), a term referring to human contributory role in conditioning the smart space and Machine Users (MU), another term describing the contributory role of machine intelligent smart devices. The processing operations utilized by EUs and MUs follow a sparse connectivity rule described by a bioengineered diffusion model (Henderson et al., 2004). This new way of reasoning about smart space application solutions and smart systems in general will open a door of seamless possibilities for next generation smart products (NGPs) both in commerce and industry; these new line of products will not just be smart, but will be very much aware of a variety of real-time experiences performing optimally in the process.

This research presents the proposed methodology of consensus-awareness as it pertain the conditioning of smart space environments; the experimental simulation results/discussions and the conclusions are also subsequently provided.

2. CONSENSUS-AWARE METHODOLOGY

This section presents the underlying theory guiding our proposed "consensus aware" (CA) concept as applied to real time smart campus beds. It includes the presentation of the core components of a CA such as: the group sensing control, heterogeneity, and probabilistic reasoning or predictive inference.

2.1 Consensus-Aware Group Sensing and Control

In our group sensing paradigm, a randomly pooled set of input objects constitute an active sensor network (ASN) while an aggregated response of input states of these objects (randomized ASN) depict the control signal. These states are interpreted first as vote signals that feed into the smart space field.

There are three main objectives in such an approach:

1) The computation of a variety of consensus experiences (or vote signal states).
2) The determination of important patterns from (1).
3) Based on information in (2), the control of conditioner state variable(s) of the ASN

The implication of these objectives is that we build a system that is aware of different consensus states or experiences. Such a system is referred to as an Active-Consensus-Aware-Conditioner (ACAC) because at any point in pooling time, only a portion of sensor objects from two or more contributory logical functions (called the active set) is considered for decision making.In the subsequent sub-section, we describe the bio-engineered sparse connectivity technique used in generating object sequences including algorithms that make this possible in finite computing time.

2.2 Sparsely connected Bio-engineered Processing

Sparsity plays a vital role in modern artificial intelligent computing systems as this reduces the burden on the computing algorithm and resources used (energy, processing space etc). This burden has been attributed to the well known 'curse of dimensionality' faced by so many conventional machine learning/intelligence systems. We use the Diffusion theory which is based on the assumption that information synthesized by some so called diffusion agents can be modelled as stripes or two-state patterns based on a simple set of morphogens (diffusion agent variables) following activation/inhibition rule (Henderson et al., 2003).

The diffusion theory presupposes that a bioengineered process is modelled by a set of reaction and diffusion features as (Henderson et al., 2004):

$$\frac{\partial c}{\partial t} = f(c) + D\nabla^2 c \qquad (1)$$

For a two variable system,

$$\begin{aligned} \frac{\partial u}{\partial t} &= \gamma\, f(u,v) + \nabla^2 u, \\ \frac{\partial v}{\partial t} &= \gamma\, g(u,v) + d\nabla^2 v \end{aligned} \qquad (2)$$

where,

$f(c)$ = bio-engineered reaction component

$D\nabla^2 c$ = bio-engineered diffusion component

u, v = bio-engineered concentrations variables (morphogens)

$f(u,v),\ g(u,v)$ = bio-engineered reaction kinetics of u, v

Instead of eqn(1-2), it is typical to use a more pragmatic solution for reaction-diffusion components/variables defined. This approach is as depicted in Algorithm 1.

Algorithm 1: Smart Space Device System Diffusion

1: Set S *as Stripes,* n *as Counter size,* k *as stripe threshold*

2: for *all stripes,* s $\in$ s.S *do*

3: a ← find (s ≡≡ n – k)

4: end for

2.3 End-User/Machine-User Concept

In our consensus-aware smart space environment, machines and human operators co-exist via a conditional contributory set of experiences. This co-existence may have two functions: sensing of the environment such as in temperature monitoring, and control of the environment such as in air-conditioning. Following the rules of sparsity described in the aforementioned sub-section, our proposed model uses an End-User logical function to model human contributory role and a Machine-User logical function to model the contributions of the smart devices. These users form the ASN model for the mining of consensus-aware states. The models are described algorithmically in Algorithm 2 and 3 for the End-User (EU) and Machine-User (MU) functions respectively while Algorithm 4 depicts a combined logical model for aggregating the consensus estimate per experience trial run.

Algorithm 2: Logic for End-User (EU) function

Initialize M_s, *as Message command parameter,* I_v, *as Vote State,* K *case.*
for *all* $m \in m.M_s$, $k \in k.K_s$ *do*
  Case: 1 $\leftarrow$ k
    if $m.M_s \equiv 1$
      $1 \leftarrow I_i$ *// Encode as 1*
      $\{I_i, 1\} \leftarrow I_i$
  Case: 2 $\leftarrow$ k
    if $m.M_s \equiv 0$
      $0 \leftarrow I_i$
      $\{I_i, 0\} \leftarrow I_i$
Store I_i *in buffer memory*
  end case
end for

Algorithm 3: Logic for Machine-User (MU) function

Initialize P_i, *as physical parameter,* I_v, *as Vote State,* T_h *as Threshold.*
for *all* $p \in p.Pi$ *do*
  if $p.Pi > T_h$
    $1 \leftarrow I_i$ *// Encode as 1*
    $\{I_i, 1\} \leftarrow I_i$
    else
    $\{I_i, 0\} \leftarrow I_i$
Store I_i *in buffer memory*
end for

Algorithm 4: Consensus mining algorithm

Initialize $I_{i(k)}$, *as MU state* L, $I_{i(k)}$, *as EU State* L, T_h *as Threshold,* K *Case,* C_s *estimate*
for *all* $I_i(k) \in I_i.L$, $k \in k.K_s$ *do*
Case: 1 $\leftarrow$ k // *Retrieving data from MU phase*
if $I_{i(k+1)} \equiv I_{i(k)}$
$I_{i(k)} \leftarrow C_s$
else
$99_{)} \leftarrow C_s$ // *99 is a dummy value*
Case: 2 $\leftarrow$ k // *Retrieving data from EU phase*
if $I_{i(k+1)} \equiv I_{i(k)}$
$I_{i(k)} \leftarrow C_s$
else
99 $\leftarrow C_s$ // *99 is a dummy value*
Aggregate (C_s)
Store C_s *in buffer memory*
end if
end case
end for

3. SIMULATION RESULTS AND DISCUSSIONS

3.1 Experimental Details and Simulation Results

The experiments have been performed in MATLAB ® software using an Intel core-i5 64-bit Windows OS, with an 8GB RAM space. The logical functions are programmed into the MATLAB system using an M-file editor and simulations have been performed for a total o 500 trials and adjusting the sequence size from 500 down to 100 in steps of 50; this gives a total of 10 different simulation results. We have also set the sparsity level at a factor of 1.4 which reduces the total number of considered randomized samples.

The simulation models a smart environment for conditioning the temperature of a classroom unit in a university campus. The mean temperature corresponding to room temperature levels and variance (both set at 28°C and 10°C respectively) are modelled as a randomized function.

The randomization function is computed using eqn(3) as:

$$R_f = \mathrm{N}(0,1) * \delta_{eu|mu} + \mu_{eu|mu} \qquad (3)$$

where,

$\mathrm{N}(0,1)$ = a uniform random number between 0 and 1.

$\delta_{eu|mu}$ = variance of vote signal amplitude of an EU or MU.

$\mu_{eu|mu}$ = mean of vote signal amplitude of an EU or MU.

In all trial runs conducted, the task is to determine the contributory role of the EU/MU phases in terms of an ON-state/OFF-state probability of aggregated EU/MU experiences. These probabilities determine the trend in pattern formation of the ACAC model and are computed using eqn(4):

$$HIGH \mid LOW_{PROB} = \frac{freq(CMA_{high|low-pattwrns})}{N_p} \quad (4)$$

where,

$CMA_{high|low-pattwrns}$ = number of EU or MU algorithm high or low patterns in a given data train of randomized encoded values

N_p = total number of patterns formed after applying sparse filtering (EU/MU) algorithm.

The results of simulations are as shown in Table 1.

Table1: Vote signal contributions of EUs

Sample Size	uo_prob_0_ON	uo_prob_0_OFF
500	0.5007	0.4993
450	0.5008	0.4992
400	0.5025	0.4975
350	0.4991	0.5009
300	0.5043	0.4957
250	0.5023	0.4977
200	0.4967	0.5033
150	0.5039	0.4961
100	0.5096	0.4904
50	0.5154	0.4846

The results clearly illustrate that higher sample sizes leads to more stability in pattern representation (i.e. the mean ON state probabilities are always greater than the corresponding mean OFF state probabilities). Another important observation is the frequencies of patterns greater than or less than 0.5 for both the mean ON state probabilities and the mean OFF state probabilities respectively. This aspect is also clearly observable by increasing the sequence (sample) size to 700 and 1000 respectively (see Fig.2 and 3 in that order). At a sequence size of 700 and at probability > 0.5, the number of histogram bars for the HIGH (ON-state) probability is 3 as against 2 for the LOW (OFF-state) probability (see Fig.1). Also, this situation is somewhat replicated when the sequence size is further increased to 1000 (see Fig.2); in this case the number of HIGH state bars is 4. Thus, as data patterns become more dilated, the tendency to stabilize at a particular direction becomes a possibility.

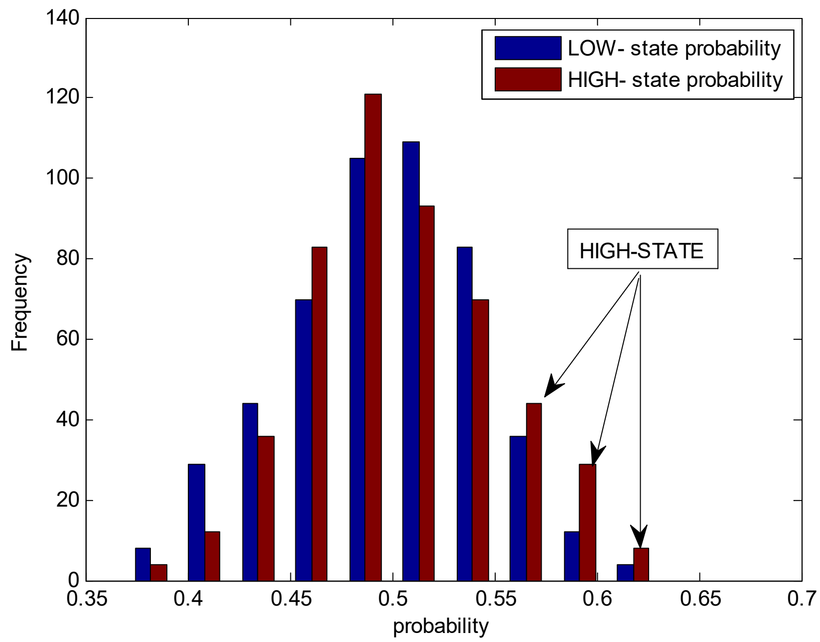

Fig 1: Simulation of CMA-type algorithm response at sequence size of 700 and at 500 trial runs.

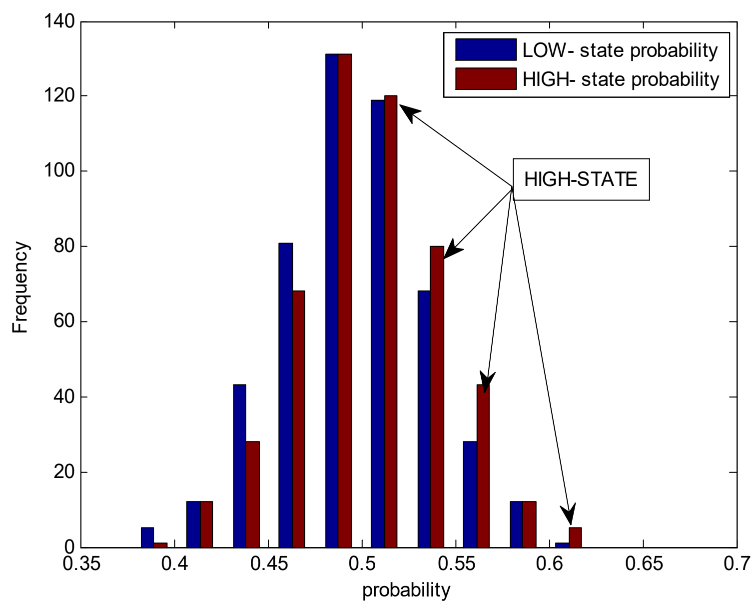

Fig 2: Simulation of CMA-type algorithm response at sequence size of 1000 and at 500 trial runs.

4. CONCLUSIONS

In this research study we have presented a novel approach to the problem of pattern deduction and formation in a smart space environment. We presented our idea of an Active Consensus-Aware Conditioner (ACAC) for smart spaces targeted at university campus testbed. The study shows that patterns of simulated temperature data can be probabilistically interpreted by considering a consensus of logical user-oriented processing functions (the EU and MU). This makes for a more consensus-aware mechanism as the contributory role of these classes of user functions ensures that the level of bias in the system is curtailed. The idea can be simulated and with some slight modifications in design adapted to real time smart campus applications.

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