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SMART-CEVA: A Real Time Implementation of a Smart Campus Evaluator and Analytic Technique based on a Hybridized Consensus Mining Algorithm

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ABSTRACT

Smart campus is a way of enriching the environment of colleges or universities with quick acting and context aware solutions. The smart campus includes devices that are usually embeddable with sensors and possibly actuators which are in turn used for ambient conditioning of the smart campus environment. In this paper, a new (hybridized) approach to smart campus conditioning is proposed. The approach is based on the idea of bio-engineered sparse feature generation for solving dimensionality issues and improving the adaptive conditioning process using consensus aware mining algorithms. A sparse learning algorithm is applied to real time conditioning of ambient space in a smart bed within a university campus environment. The conditioning results indicate promising prediction results via the special consensus-aware mechanism. The results of simulations further validate the unique ability of CMA-type algorithms to generalize more precise condition state representations as the number of sequences and evolution trials increase.

Keywords: Context-awareness, consensus mining, smart campus, smart conditioning, sparse learning.

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1. INTRODUCTION

Humans tend to react to the environment in a manner that requires a sensual perception of things both animate and inanimate. In the world of perceptual computing, the requirements of sensory processing of data is not an exception and is a fundamental requirement for building smart spaces – an environment conditioned by smart devices. The devices of the smart space (smart space devices or SSDs) typically build a rich and interactive environment that pervades most human and non-human entities. In recent times, smart space research has centred on building interactive environments for campuses. An important reason for this is to leverage the existing technologies for pervasive computing to build useful services. Some innovative researches in these areas include the development of smart campus scheme for real time control and energy management of electrical and electronic devices with intelligence functionality [1], predicting electricity consumption in 7 university buildings using Auto-Regressive (AR) technique [2], the use of near field detection algorithms and a hierarchical procedure for detecting nearest and free car parking spots in a university campus [3] and Trail-Care, a pragmatic context-aware scheme used for real-time support of wheelchair users has been proposed in [4].

Most campus wide operations demand intelligent, accurate and timely decision making functions for potentially installed SSDs in real time; the intelligent aspect demands that predictions of possible future states is carried out with as minimal as possible

There is an obvious gap, however, as most researches focused on simulations rather than real time implementations; even where real time solutions were proposed, there is lack of clarity on the actual implementation details and the results obtained thereof including limited or zero intelligent prediction functionality. More recently, there has been renewed attention in the use of group learning or consensus mining (via a voting mechanism) and machine learning applications in real time embedded applications for smart campuses and in Activity Daily Living (ADL) smart designs. For instance, the research study conducted in [5] used the k-Means algorithm for classification of simulated End-User (EU) thermal conditioning votes and occupant tracking in a smart campus room unit; the k-Means uses data clustering to automatically group similar data entries that belong to a computed cluster centre. However, the k-Means suffer from the "curse of dimensionality" so it may take a large number of iteration runs to find a solution centre. Another serious drawback related to the first is that in the k-Means technique, there might not be found similar entries making it computationally inefficient. In addition, the consensus approach proposed in [5] does not include a bio-inspired sparse learning scheme.

Another recent and similar research in the context of ADL has also been presented in [6], where a minority and majority voting scheme was used to build behavioural trust among nodes in an ensemble of training data values. This approach just as in the aforementioned does not integrate bio-inspired sparse learning rules.

In this paper, a novel and computationally efficient approach based on consensus mining in the context of End-User-Machine-User (EUMU) votes is proposed for real time conditioning experiments. The proposed technique further applies the idea of a biological inspired (bio-engineered processing) based diffusion theory which favours a morphogenetic process of sparse generation and predictive computations of features for dimensionality reduction [7] and this technique has been applied to a smart test bed implemented in [8]. In the sections that follow we present our embedded-soft computing approach coined SMART-CEVA, the experiments on real world data and our results.

2. PROBLEM STATEMENT

Currently, there is a gap in the literature accounting for the evaluation and analysis of smart campus solutions in real time test beds. One of the reasons of this may be due to the complex nature of facilities within most campus environments and primarily due to hardware interfacing restrictions as SSDs are usually required in such solutions.

The existing approaches are mostly simulation-only and the implemented solutions are generally vague lacking in essential details. Most are also lacking in the feature of making consensus predictions about data in real time. Thus, smart campus solutions that are consensus-aware and prediction-capable will be an obvious advantage.

3. METHODOLOGY

In this section, the approach based on sparse consensus mining for the smart campus evaluation and analysis (SMART-CEVA) is presented. This approach makes use of an open source framework, Arduino® [9], and is modular in structure. The model incorporates the core tenets of an Arduino Embedded Microcomputer System (AEMS); it is robust, modular and customizable.

3.1 Theoretical Foundations

SMART-CEVA is based on two main concepts: the theory of diffusion as introduced in [7] and the principle of consensus mining which is widely applied in the cryptocurrency field [10-12], generally known in the field of information sciences, computing and industrial systems modelling in the context of group learning [13-16] including application in wireless sensor networks [17, 18] but not popular or unknown in the field of smart campus research. The diffusion theory makes the assumption that information from signal processing agents (called diffusion agents here) can be synthesized as stripes or two-state patterns based on a simple set of morphogens (diffusion agent variables) using an activator-inhibitor rule [8].

On the other hand, our consensus mining technique enables the realisation of a robust decision based on End-User and Machine User input vote signal inputs. By End User (EU), we refer to the to the participation of real human users interfaced to a microcomputer system via remote or local logical operations; in the same vein, a Machine User (MU) refers to the participation of real time embedded sensors interfaced to a microcomputer system via remote or local logical operations. The EU and MU represents the agents of diffusion and they follow a sparse generative rule described in the following sub-sections.

The vote signals of both agents are typically encoded as binary signals.

3.2 Smart Space Conditioning Technique

In the context of smart space conditioning, we may define an environment that comprises of a set of smart space objects as follows:

$$E = \{O_{b(1)}, O_{b(2),\ldots,} O_{b(n)}\} \qquad (1)$$

such that,

$$\begin{aligned} & O_b \in H_u \mid O_b \in D_s \\ & \qquad \Rightarrow E = \bigcup (H_u, D_s) \end{aligned} \qquad (2)$$

where,

O_b = the set of smart space objects

H_u = the set of person objects

D_s = the set of smart device objects e.g. sensors or actuators.

The smart space may be referred to as a collection of smart device objects which may be sensors or actuators and human objects within an environment. In reality, however, the model in (2) is typically constrained by a pre-scribed finite boundary point as denoted in (3) as:

$$E = \bigcup_{lb}^{ub} (H_u, D_s) \qquad (3)$$

where,

ub, lb = are lower and upper bounds

If the smart device is storing information temporally, overtime it becomes dilated with enormous information; if under peculiar circumstances, there is a drift in pattern, a smart device may initiate an interrupt. Thus, instead of storing these enormous patterns, the device only stores the interrupting signals thereby reducing storage requirements by intelligently storing only useful causes of patterns. The principle behind this useful operation is termed the “diffusion theory” or mixture analysis.

If we model a smart sensor device system as a bioengineered process, then the reaction and diffusion features may be modelled as in [7] as: $\frac{\partial c}{\partial t} = f(c) + D\nabla^2 c$ *(4)*

For a two variable system we have,

$$\begin{aligned} \frac{\partial u}{\partial t} &= \gamma\, f(u,v) + \nabla^2 u, \\ \frac{\partial v}{\partial t} &= \gamma\, g(u,v) + d\nabla^2 v \end{aligned} \qquad (5)$$

where,
$f(c)$ *= the reaction component*
$D\nabla^2 c$ *= the diffusion component*
u, v *= the concentrations of the variables (morphogens)*
$f(u,v)$, $g(u,v)$ *= the reaction kinetics of* u, v

For practical considerations, the models in eqn(4-5) may be replaced using diffusion directly; this is described by the threshold operation of Algorithm 1.

Algorithm 1: Smart Space Device System Diffusion

```
Set S as Stripes, n as Counter size, k as stripe threshold
for all stripes, s ∈ s.S do
    a ← find (s ≡≡ n – k)
end for
```

3.3 Smart Space Consensus Mining Model

The smart space may be modelled as a sequence or activity data capture system. This kind of system captures two primary entities:

1. *An end user (EU) who based on experiences sends in a sequential manner prescribed commands to a smart device to adjust the smart space environment.*
2. *A machine user (MU) which based on sensory information adjusts the smart device controls and in the process adjusts the smart environment.*

In SMART-CEVA, communication between the EU and MU within the smart space is done in the smart device unit (SDU) based on the Arduino microcomputer – an embedded microcomputer device with an autonomous or semi-autonomous capability.

Sensing and collation of control (command) signals from the MU and EU in the SDU is done in a consensus using the logic in Algorithm 2.

Algorithm 2: Consensus mining algorithm

```
Initialize $l_{i(k)}$, as MU state $L$, $l_{i(k)}$, as EU State $L$, $T_h$ as Threshold, $K$ Case, $C_s$ estimate
    for all $l_i(k) \in l_i.L$, $k \in k.K_s$ do
        Case: 1 $\leftarrow k$    // Retrieving data from MU phase
            if $l_{i(k+1)} \equiv l_{i(k)}$
                $l_{i(k)} \leftarrow C_s$
            else
            $99_{)} \leftarrow C_s$    // 99 is a dummy value
        Case: 2 $\leftarrow k$  // Retrieving data from EU phase
            if $l_{i(k+1)} \equiv l_{i(k)}$
                $l_{i(k)} \leftarrow C_s$
            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
```

The consensus mining activity is as depicted in Fig.1.

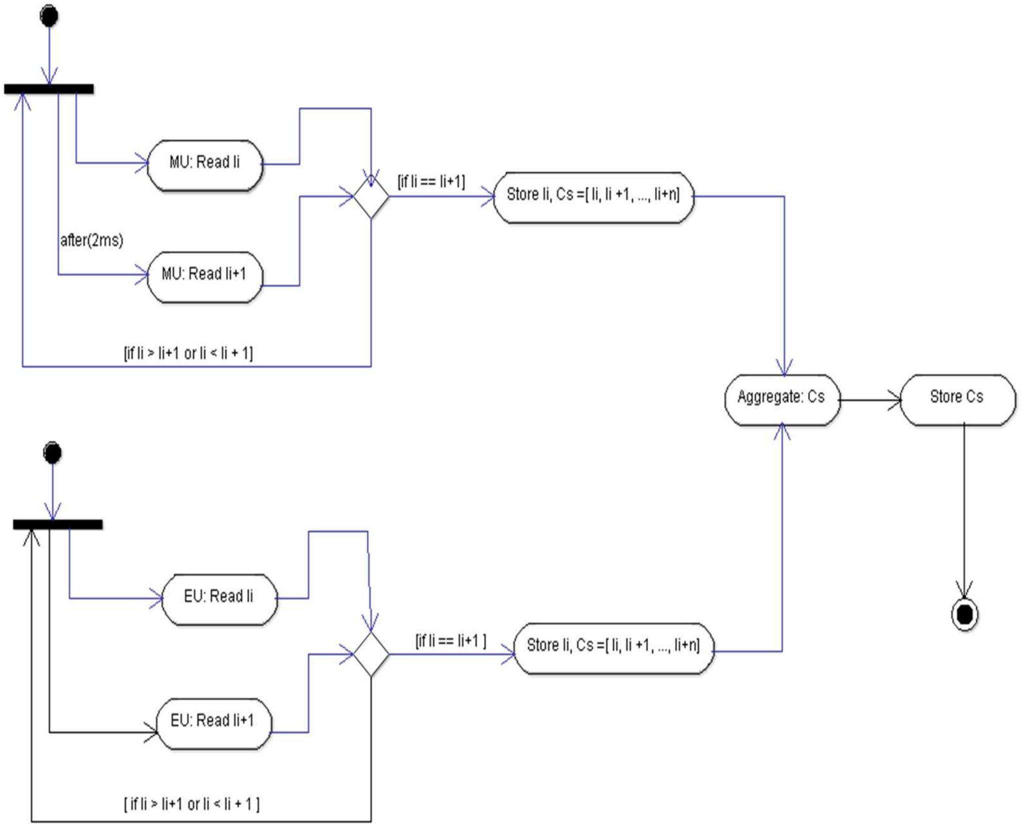


Fig.1: Consensus Mining in SMART-CEVA

3.4 Consensus Prediction Technique

The contributions from an EU and MU typically aggregated by performing a statistical operation on the concatenation of vote signals from both users using a consensus mining algorithm (CMA) as provided in Algorithm 2. In the present research, we have defined a probabilistic prediction of consensus to mean a ratio of the frequencies of 1's in the data train captured temporally to the maximum number of considered data points after sparse filtering.

Here, the 1's refer to room users report of poor temperature conditions (in the case of EUs) and deviations from expectation threshold (in the case of MUs). The probabilistic prediction is given in (6):

$$HIGH_{PROB} = \frac{freq(CMA_{high-pattwrns})}{N_p} \qquad \textbf{\textit{(6)}}$$

where,

$CMA_{high-pattwrns}$ = number of CMA-type algorithm high patterns in a given data train encoded values

N_p = total number of patterns formed after sparse filtering.

If the value of $HIGH_{PROB}$ is greater than 0.5, then an external conditioning is required to bring the room to desired temperature state, otherwise the room conditioning is just sufficient.
The way the CMA computes the net predictions are determined by the embedded software developer. In this study, we have used the average of the computed $HIGH_{PROB}$ values from both CMA-EU-type and CMA-MU-type algorithms. Thus, the final prediction is basically an agreement between EUs and MUs.

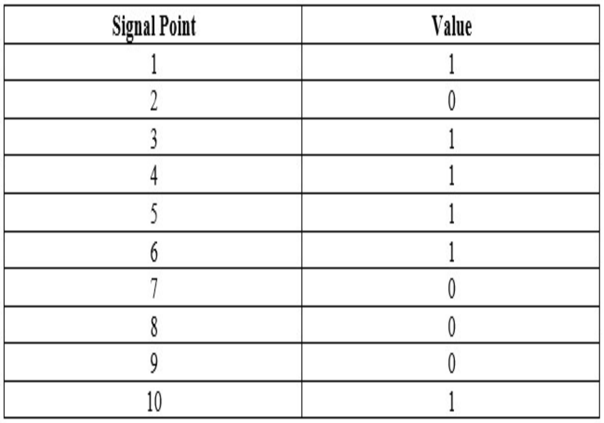
4. RESULTS

4.1 Hardware Emulation Experiments

In this section, we illustrate our idea using a real time implementation of SMART-CEVA application and hence emulate its consensus-aware capabilities while leveraging on existing embedded technologies such as Arduino. In this section, the task is to monitor the room temperature of a classroom unit in the University of Port-Harcourt environs located in Rivers State, Nigeria, using EUMU consensus approach. We set the baseline probabilistic prediction criterion as 0.5 and the number of desired training points to 10.

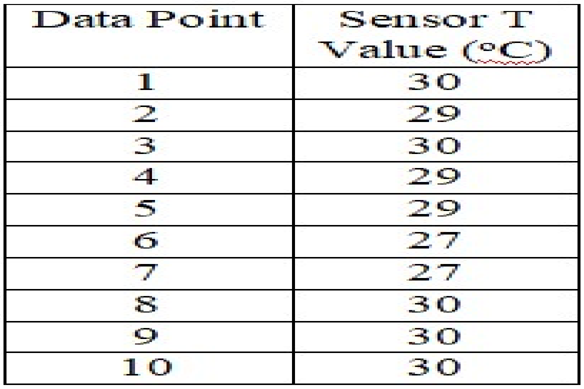
In Table 1, the vote signal contributions of the EUs are as shown; here a 1 imply a need for conditioning. Based on this information, the calculated HIGH-state frequency probability contribution of EUs is 0.6. In Table 2, the acquired temperature sensor readings from embedded sensor is depicted. Here, the threshold for activation is set at 27^{o}C. Based on this requirement, the resulting values as computed by the MU are as shown in Table 3. Using this information, the calculated HIGH-state frequency probability contribution of MUs is 0.8. The estimated or predicted joint probability is 0.7; but 0.7 is greater than the base value. Thus, the system will predict a need for conditioning.

Table 1: Vote signal contributions of EUs



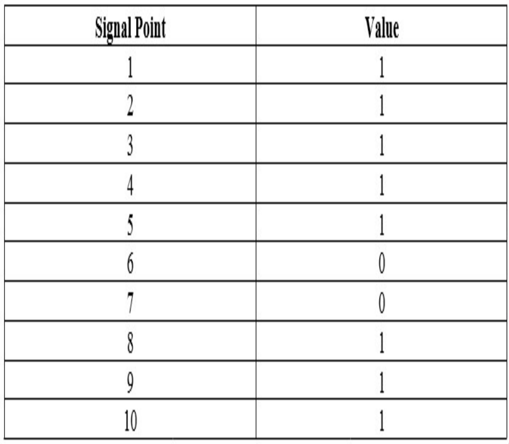
Signal Point	Value
1	1
2	0
3	1
4	1
5	1
6	1
7	0
8	0
9	0
10	1

Table 2: Temperature Sensor Readings of MUs



Data Point	Sensor T Value (°C)
1	30
2	29
3	30
4	29
5	29
6	27
7	27
8	30
9	30
10	30

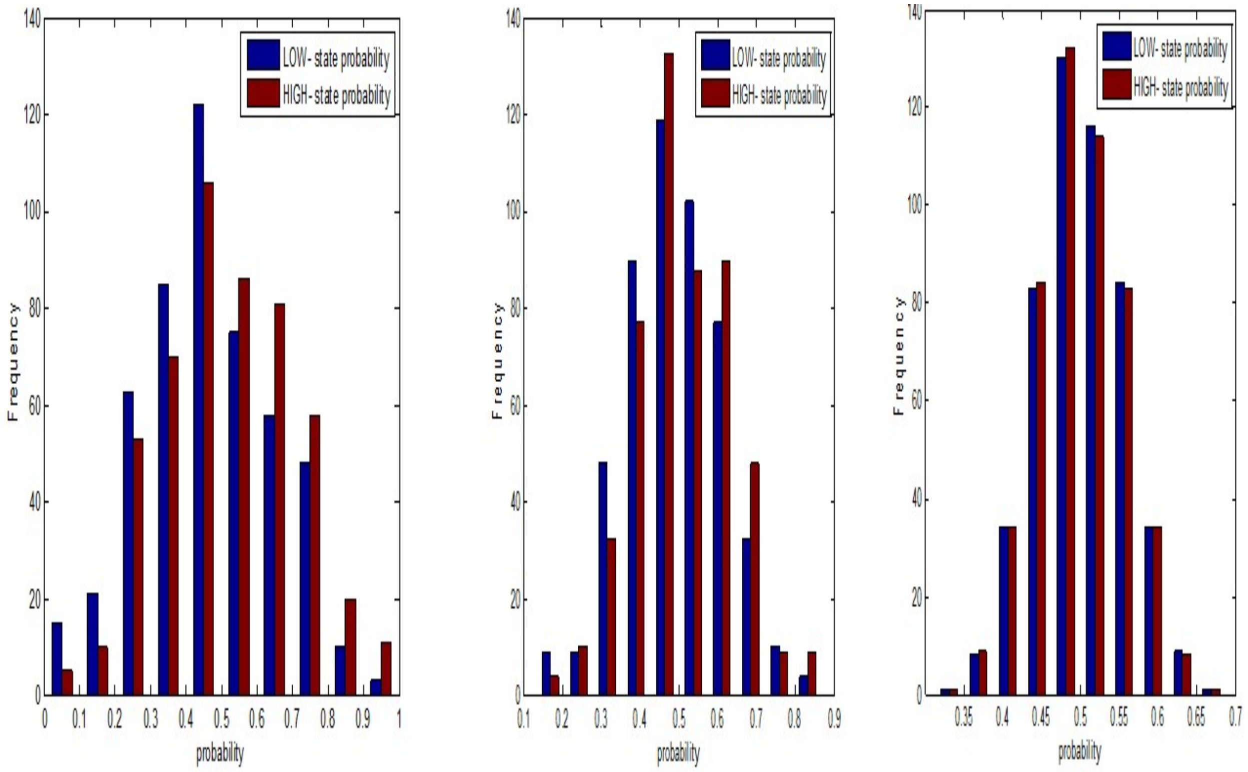
Table 3: Vote signal contributions of MUs



Signal Point	Value
1	1
2	1
3	1
4	1
5	1
6	0
7	0
8	1
9	1
10	1

4.2 Simulation Experiments

In this section, we show by simulations the effect of large numbers while using SMART-CEVA for data filtering. In Figures 2(a-c) is shown a histogram trend prediction analysis simulation of synthetically generated data using the proposed CMA-type algorithms. The plots are captured for different sequence size and evolution trial runs in order to identify useful patterns.



a) 50 by 100 b) 100 by 500 c) 500 by 500

Fig 2: Simulation of CMA-type algorithm response at differing sequence size and trial runs (size by evolution trial run).

5. DISCUSSIONS

The results of experiments using SMART-CEVA shows that it is possible to emulate bio-inspired processing in real time environment. From Table 1 and 3, it is clear that there will always be variation in response (vote contributions) of both EUs and MUs; nevertheless, a consensus will always be arrived such that the actual activation state (start conditioner) will reflect a reasonable cause such as the high temperature variation. It is important to emphasize here that the number of MU vote signal acquisitions must match the number of EU vote signal entries; the vote signal contributions of both users must also be sparse. From Fig.2a, the low state probability has a higher priority over the high state probability on the average probability span of about 0.5 when the sample size is set at 50 and the evolution trial runs at 100; the high state probability will however gain in priority over the low state probability at a much higher than average probability when the probabilities are at about 0.55, 0.65, 0.75, and 0.85.

In Fig.2b, this situation is somewhat replicated but with some distinctions at a probability of about 0.55 and 0.75 when the sample size is increased from 50 to 100 and the trial runs increased from 100 to 500.

In Fig.2c, the competition between the low and high state probabilities is less evident due to a diffusion of input signals as the sample size is increased to 500 and trial runs set at 500.

Simulations also indicate that that sparse learning representations of a mixture of threshold conditioned signals gives rise to a more diffuse representation of the data signals allowing the intelligent storage of only useful vote signals that caused the underlying data pattern.

6. CONCLUSIONS AND FUTURE WORK

In this research study we have presented a new approach, SMART-CEVA, for analysing a smart space environment within a university or college campus. The approach is based on a hybridization of bio-engineered processes with consensus mining to build a sparsely connected consensus-aware smart space solution. We performed emulations in a real time test bed and obtained satisfactory results. However, there is still a need to generate very large number of experiments in the study environment in order to decipher important patterns or trends in real time and hence validate our simulations. This is left as a future work.

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