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ANALYSIS OF DATA BASED ON CLINICAL ASPECTS IMPLEMENTING META-HEURISTIC APPROACH: A CASE STUDY

ANALIZA DANYCH DOTYCZĄCYCH ASPEKTÓW KLINICZNYCH Z WYKORZYSTANIEM PODEJŚCIA METAHEURYSTYCZNEGO: STUDIUM PRZYPADKU

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Abstract: The application of information technology, particularly in health science in the present situation, is provisioned with intelligent applications along with automation to minimize the associated cost and enhancement of the facilities. Although the experimentation associated with the microorganisms may be a part of pathological aspects, it cannot be constrained at one specific location. Yet again, the same may be diversified widely in large geographical locations based on applications and utilities. The inclusion of computational intelligence along with complete advanced technical support is very necessary to overcome these difficulties and support the linked base stations for archiving optimum signals through the deployed sensors. In short, sensors can be used to translate the parametric values of accumulated data into signals which can also be analyzed and monitored. In this work, a specific meta-heuristic technique is implemented, focusing on the accumulation of sensors and the response time for accumulation of data.

Keywords: clinical data, deployed sensor, virtual machine, swarm, processing elements.

Streszczenie: Zastosowanie technologii informatycznych, szczególnie w naukach o zdrowiu w obecnej sytuacji, bazuje na inteligentnych aplikacjach wraz z automatyzacją w celu zminimalizowania związanych z tym kosztów i ulepszenia służby zdrowia. Chociaż eksperymenty związane z mikroorganizmami mogą być częścią zagadnień patologicznych, nie można ich ograniczać do jednej konkretnej lokalizacji. Wykorzystanie narzędzi i aplikacji na szerszym obszarze geograficznym może być bardzo zróżnicowane. Zastosowanie inteligencji obliczeniowej wraz z pełnym zaawansowanym wsparciem technicznym wydaje się konieczne, aby przezwyciężyć trudności i wspierać połączone stacje bazowe w celu archiwizacji optymalnych sygnałów za pomocą rozmieszczonych czujników. Czujniki zatem mogą służyć do przekształcania wartości parametrycznych zgromadzonych danych na sygnały, które można również analizować i monitorować. W artykule zaimplementowano specyficzną technikę metaheurystyczną skupiającą się na akumulacji czujników i czasie odpowiedzi na akumulację danych.

Słowa kluczowe: dane kliniczne, wykorzystane czujniki, wirtualna maszyna, rój, element przetwarzający.

1. Introduction

Linked data can be provisioned with better performance during their applications on virtual platforms. The implementation through the virtual platforms with associated sensors for these applications can be successfully directed towards obtaining the solutions and fulfilling all the requirements. As the technology linked with the Internet of Things has been proved to have optimal applications at all levels, in such situation it can be added to attain smarter solutions as far as the health issue is concerned. The components and devices associated with the present system can help to accumulate the desired largescale data from the sensors and process them towards obtaining optimality at every stage. The embedding of the computational hardware such as deployed sensors and other peripherals can be uniformly deployed to maintain synchronisation. Similarly, the usage of distinct sensors in the clinical applications, especially in those pathological and microbiological, can make the diagnosis of the symptoms very simple. The combination of virtualisation mechanisms with the applications linked to the Internet of Things can produce the clinical applications as well as the diagnosis of the symptoms, in the proper manner, supporting the real-time applications associated with the largescale data. Even though some challenges or constraints may be expected during the accumulation of the data, yet provisioning the security parameters as well as these privacy mechanisms can be resolved attaining the effective solutions. In this situation the scheduling of tasks is also required on the basis of either priority-based scheduling or non-pre-emptive scheduling mechanisms. In the former, importance should be given to the sensitive tasks with optimum priority,but in the case of the latter, each and every assigned task will have equal quantum of processing intervals. The sensor nodes linked with the system can then be reconfigured prioritising the related activities. However, the deployment of dynamic power management in such a situation can be associated with challenges such asthe consumption of more power during transition along with a delay response. The protocols associated with the sensors should be also be responsible for synchronising the timing signals in both the deployment and the synchronisation stages. Naturally, in the deployment stage, the unique identification of the sensor as sender is maintained and in the synchronisation stage, the synchronisation among all the sensors at each level is maintained based on the time stamp. In all respects, the provision on locating the sensors at random should also be accommodated towards the accumulation of sensor data. While prioritisation is being given on virtual diagnosis linked to clinical or pathological or microbiological aspects, generally the proper accumulation mechanisms of subsequent data with applied data analytics techniques should be performed and, if possible, simulation mechanisms can be also adopted for obtaining optimality or near optimal results. The primary intention in such a situation is not only confined towards managing the functional tasks, but also prioritising the mechanism of analysing data based on inference. The mapping procedures within the data sets accordingly can be implemented for achieving the requirements as desired within the system. Next, the process of simulation on the accumulated data through the deployed sensors can be applied using computational intelligence mechanisms to measure the actual performance along with the parametric values.

2. Review of literature

P. J. van Diest et al. (2019) focused on digital pathology and analysed the merits and challenges associated with clinical and digital consultation on pathological analysis. Moreover, they observed the necessity of digital pathological consultation particularly in virtual independent platforms.

S. Benjamens et al. (2020) discussed different machine learning and artificial intelligence applications linked to internal medicines as well as clinical pathology. In fact they observed that pathological applications associated with computational intelligence can also be embedded into routine pathological aspects.

M. Rosenfield et al. (2011) made the comparison with the issues of occupational health aspects with implementation mechanisms linked to digital pathology. Obviously, the non-featured health issues as well as accumulation of unstructured feedback associated with digital pathology can also be optimised with the dynamic deployment of associated sensors.

A. M. Rossignol et al. (1987) focused on the enhancement of a chronic villus sampling test, which is a prenatal test, and intended for digitalization with computational analysis, and observed its economic impact.

M. Chui et al. (2016) concentrated on digitalization aimed at making digital pathology more transformative. In fact, they observed the fruitful implementation of artificial intelligence in digital pathology. They have also emphasized the complete automation factoring cost, and the regulatory as well as the social acceptance considerations.

C. Turnquist et al. (2019) analysed the cost effectiveness of the comparable data based on standardized criteria, and focused on the implementation based on digital pathology in their application.

J. Griffin and D. Treanor (2017) prioritised the efficiency of digital pathology from the point of view of cost during the primary diagnosis. Their study also focused on productivity enhancement and compared it with clinical pathology.

J. Ho et al. (2014) examined cost-efficiency linked to digital pathology, and compared it with clinical pathology considering and assuming treatment expenses in the distributed health network.

N. Stathonikos et al. (2019) studied the digital pathology as an ergonomic issue. They focused on musculoskeletal aspects and equivalent symptoms with similar frequency, and prioritised the implementation of digital pathology.

S. Thorstenson et al. (2014) studied ergonomics linked with digital pathology. They intended to prioritise a chronic villus sampling and issues associated with primary histo-diagnoses.

3. Examples

3.1. Example 1

Figure1 presents the timing constraints and the synchronisation of signals associated with the sensors. Initially, transmission of the signal is initiated from sensor location-1 time stamped with timing signal, t1 towards sensor location-2. After the receipt of the signal at sensor location-2, sensor location-2 immediately sends the reply signal with the timing signal, t3 along with earlier recorded timing signals t1 as well as t2. This signal can be accumulated by the sensor location-1 at timing signal, t4. Note that timing signals t1 and t4 are prioritised based on the sensor location-1, whereas timing signals, t2 and t3 are based on sensor location-2.

Figure 2 illustrates the localisation of sensors based on range with measured angles. Specifically, it is based on the accumulation of angles from all the locations associated with the sensor nodes towards prioritising the location of sensors. As shown in Figure 2, there are three deployed sensors, i.e. sensor-1, sensor-2 and sensor-3 associated with angles (theta1, theta2 and theta3). In such situations, the relationship among these sensors can be estimated by theta*(xi, yi)+sd*theta, where i=1 to 3, theta corresponds to theta1+theta2+theta3, and sd is the standard deviation linked to the transmission of signals from sensors.

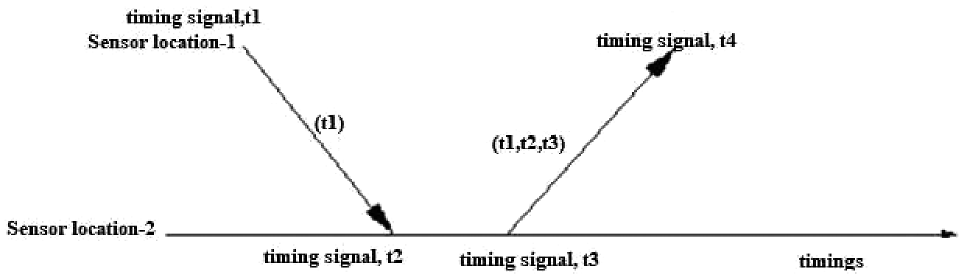

Fig. 1. Timing constraints and synchronization during transmission

Source: self analyzed.

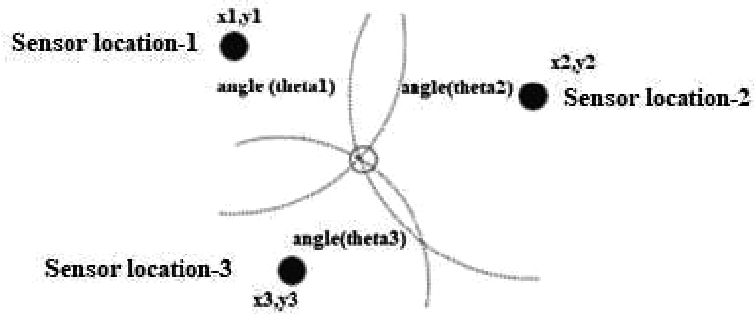

Fig. 2. Localisation of sensors based on range with measured angles

Source: self analyzed.

3.2. Example 2

Usually the analysis of data with specified applications is carried out implementing its parametric values long before instantiation and the achievement of significant results. In such cases, application of the constrained data can result in several parametric values during the analysis. Frequently, the virtual computation can be used to manage such applications provisioned with scalable storage along with processing services as shown in Figure 3. Accordingly, the mechanisms linked with the system can help to measure the execution paradigm of largescale data in virtual system. In fact, it is required to opt for the containerised datasets along with the task queues, maintaining the complete status of tasks along with accessibilities. With the expectation and anticipation of the availability of the virtual machines, the tasks are required to be executed analysing the datasets and monitoring the predetermined status.

Yet sometimes it can be seen that during the parameterisation application on data, the independent tasks submitted in the virtual platform can be executed maintaining synchronization. Similarly, while projecting on predictive analysis of some portion of clinical data, sometimes the divergence of accumulation of sensor signals may generate complicacies in aggregation and integrity of data. However, these can be sorted out applying the supervised learning mechanisms.

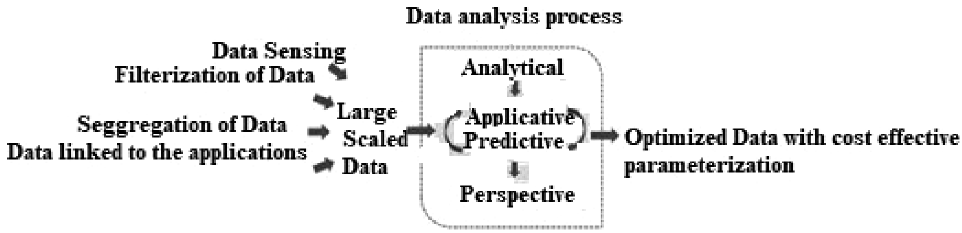

Fig. 3. Process of analysis of data with cost-effective parameterization

Source: self analyzed.

As shown in Figure 4, although the virtual computation is responsible for the enhancement of the application on large scale data, still some specific applications linked to virtual computation are quite uncommon. In fact, the solutions linked to the applications can be obtained for the large number of servers to be operated independently from different locations, may be shared or non-shared, but in all respects, they can be relocated with obviously dynamic resources. The proper management of resources is the prime factor towards obtaining optimality while analysing large scale data. The usage of the virtualised resources during active operations also focuses on optimal or near optimal cost factors. In some situations, resource management is a big challenge due to the complexities in some sensor nodes, as well as the utilisation of processing elements, along with storage allocation during the application of large scale data. Other challenge may be faced due to the origination and processing of data with heterogeneity accumulated from various sources, including deployed sensors. Therefore, to enhance the performance, the computational resources should be provisioned with efficient computing

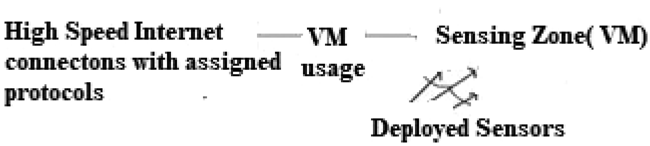

Fig. 4. Usage of virtual machine in sensing zones

Source: self analyzed.

environments. Instead of the internal storage of sensitive data, it should be more focused on the storage of large scale data in virtual platforms with global links and proper security measures.

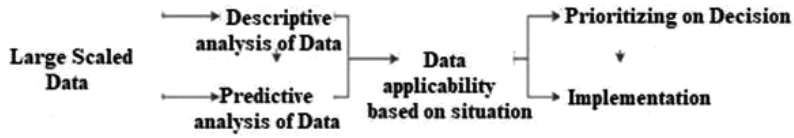

Fig. 5. Applicability of data based on situation

Source: self analyzed.

In general overview, it was seen that among the predicted data, a major portion are unstructured and can be provisioned with a lesser amount of structured data. In such a situation, the large scale data set can be challengeable due to the constraints associated with the mechanisms, along with the linked computational resources. Therefore, it may be desirable to unlock the potentiality of data and initiate the process utilisation techniques on these large scale heterogeneous data to apply in main stream as shown in Figure5. Naturally, scaling is also more focused on the application of these large scale data, as it is needed to measure the storage allocation, range of parallel, and computational mechanisms.

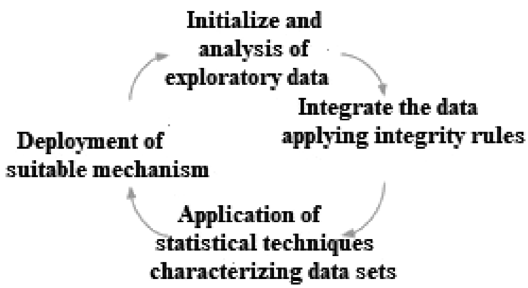

Fig. 6. Characterisation of data sets with integration

Source: self analyzed.

As shown in Figure 6, initialisation with proper analysis of the exploratory data is truly essential for obtaining the integrity of data. To maintain consistency on data, scalability with referential integrity on data is the prime concern. Sometimes, to face the challenges, the identification of exploratory large scale data is required. Additionally, specific data exploration tools may also be needed to satisfy the requirement for the analysis of large scale data sets. This seems to be the primary step linked to process data, and accordingly, some statistical techniques may be applied to characterise the data with accuracy and to obtain the optimal result.

4. Application of particle swarm optimisation

It is understood that particle swarm optimisation is a meta-heuristic approach and is highly effective in obtaining optimality or near optimal solutions for problems linked to large sets of domains. Basically, it is quite different from the classical optimisation techniques to achieve the possible solutions. The new location of each and every particle can be obtained through velocity reflecting the global best, as well as the local best linked to particle coefficients. One of the choices in such a situation is to focus on local parametric measures to obtain a better local minimum with accuracy, and focus on accumulating near optimal values.

4.1. Steps towards accumulation of trained data from sensors

Step 1: Initialise the sensors and generate the sensor_id, sensor_private_key
Step 2: Set the acquired time with the clinical data, i.e. [trained_clinical_data, acq_time]=sensor_read(sensor_id, key_id, acq_data)
Step 3: for i=1:100
acq_time(i)=trained_clinical_data(pow(2,7)*i); end
Step 4: for i=1: sizeof(trained_clinical_data) sensor_read(i)= double(acq_time(i) * normalise(acq_data); end

4.2. Steps for adoption of particle swarm optimization (simulation of swarm movements)

Step 1: Initialise the iteration levels, and counter of iteration, Cit
Step 2: Assign the coefficient factor, 3.0
Step 3: Assign the size of swarm, 47
Step 4: Initiate and process the position of swarm while (Cit<max_generaration ||!(eof)) do
Cit =1
for i= 1: 11 for j= 1 : 11
swarm(Cit,1,1)=i;
swarm(Cit,1,2)=j;
Cit = Cit+1;
end end
Step 5: Evaluate and update the position of swarm(prioritizing global best,gbest) for i=1 : size_swarm
(temp_alloc,gbest)=min(swarm(:,11,1));
end

4.3. Steps to sampling of signals and coefficient spacing

Step 1: Accumulate the sensor_signal, i.e. [sensor_signal, qs]=audrino_acc('E:\sensor_data\qs.wav') Step 2: Normalise the coefficient parameter, param_sensor_signal= sensor_signal/max(sensor_signal)
Step 3: Estimate the coefficient spacing parameters and apply the filter mechanism [y,x]= sensor_signal(4,7,47, 3.0) sample_data = rand(100,1) param_sensor_signal= filter(y,x, sensor_signal)
Step 4: Set the sampling_value=100 sampling_coefficient_spacing_value= sampling_value*qs/100
Step 5: sampled_sensor_signal= regen(param_sensor_signal, sampling_coefficient_spacing_value)/sample_data

4.4. Algorithm for regulating data based on adaptive mechanism

Step 1: Initialise the swarm variables and size population
Step 2: for i=1 : size_population
Set x(i) particle in intervalof [xmin, xmax]randomly Set v(i) velocity in interval of [vmin,vmax]randomly particle(i)=x(i) endfor
Step 3: Determine the global best position of particle, gpbest and worst time complexity
Step 4: Initialise the constrictionfactor, cfact=1 while(!(termination_condition)&&(i<size_population) i++; cfact=cfact+ coefficient factor;
Step 5: Determine the diversity factor of swarm variables linked to size_population
Step 6: Update the velocity based on present situation and calculation
Step 7: Update the position of particles and re-estimate the size_population

5. Experimental analysis

The deployment of processing elements properly equipped with sensors can be quite sufficient in some particular applications for the accumulation of data. The ability of the applied devices can be enhanced with the data processed either locally or globally. In fact, this depends on the applied architecture, i.e. centralised or distributed. Prioritising this issue, as reflected in Figure 7 and Table 1, in some situations the processing elements have the advantage of processing only very few data locally associated with central servers. Occasionally, the sensor data in real time situations can face challenges because of its routine work, i.e. processing the sensor data, linking with other sources of data and also filtering noise as well as distortion from data. However, when analysing the integral part of data and applying suitable mechanisms, these can be also easily sorted out.

Table 1. Deployment of processing elements with sensor data

Sl. No.	Deployment of Processing Elements	Accumulation of Sensor Data(m. sec.)
1	16	0.19
2	29	0.22
3	34	0.27
4	47	0.34

Source: self analyzed.

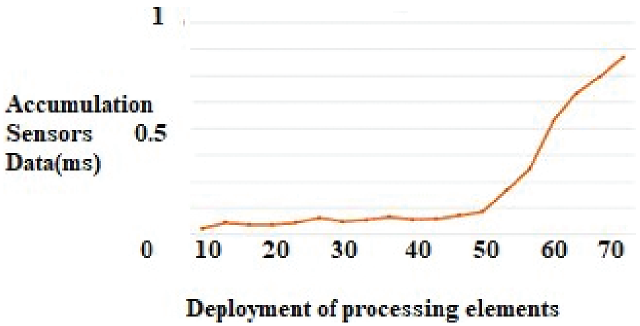

Fig. 7. Deployment of processing elements with sensor data

Source: self analyzed.

The sensors are basically implemented to measure the different properties linked to various applications in the environment. Hence, for querying and the storage of large scale data, sensors can be deployed. In fact, to minimise the computational as well as storage cost of large scale data during processing, the sensors can be deployed to measure the response time, as shown in Table 2 and Figure 8. The use of sensors also enhances the ability to analyse and to make diagnoses of real time large scale data in an efficient manner.

Table 2. Deployed sensors with the response time for the accumulation of data

Sl. No.	Number of Deployed Sensors	Response Time (m. sec.)
1	19	0.11
2	24	0.29
3	37	0.34
4	44	0.47

Source: self analyzed.

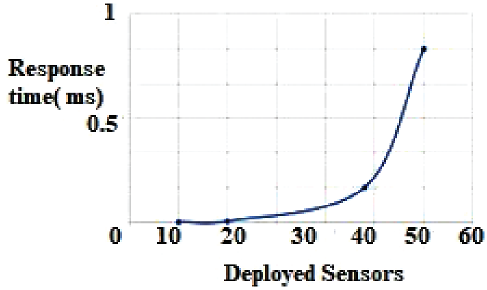

Fig. 8. Deployed sensors with the response time for the accumulation of data

Source: self analyzed.

6. Discussion and future direction

While implementing the computational mechanisms for the deployment of sensors with processing elements it can be seen that the applied approach maintains systematic interpretable steps to permit the necessary scrutiny and generate confidence in this technique. Naturally, not only the existing performance but also a proper explanation is required to achieve optimality in this process. Actually, the adoption of supervised learning schemes can enhance the existing performance and also help to maintain consistency in the accumulation of output data, which may in return correlate with the clinical parametric data. In addition, adequate parameters during application and approximation are required to be defined based on the analysis of clinical data with cost effectiveness.

7. Conclusion

In general, the optimality in the accumulation of processing elements for the storage and analysis of large scale data requires a clear distinction of the problems with appropriate solutions. Sometimes the optimality may not be linked with the combined computational components. In such situations, the anticipation of virtual computing capabilities can be helpful in the implementation of the same at a low cost along with high potential computational calculations aimed at obtaining optimal or near optimal local solutions. It is clear that the sensors can be used to analyse and translate the parametric values of accumulated data into signals. Additionally, the major role of the sensors, particularly in health-monitoring issues, is to accumulate the specific clinical data with suitable relevancy. In this regard, there must be some provision for the integration of sensors into sharing mutual linked data. In this application, a specific meta-heuristic technique was implemented to focus on the accumulation of sensors with the response time for the accumulation of data.

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