Intelligent Health Care – A Motion Analysis System for Health Practitioners

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***Abstract*—In the proposed work we present a combination of two paradigms: Wireless Sensor Networks (WSN) and Computer Vision applied for Motion Analysis. In this work the Computer Vision provides high-level behavioural monitoring and analysis, whereas Wireless Sensors capture detailed parameters of a moving object. Fusion of sensory information received from both types of sensors provides micro-level and macro-level details. These combined details can be used in various application areas. In considered applications, one of the areas can be Robotics. In this case this strategy can be used to monitor health of robots under certain actions and situations. Another important application domain is health care and rehabilitation of injured persons. In this application, movement of an injured body portion is measured after its treatment. Apart from the analysis of motion we also propose optimized movement advice to patients. Optimum motion advice is very useful in case of sports injury to recover strength and performance. In this paper we produce experimental work performed by simulating different movements of hands and legs in free space. The experimental simulation provides a broad range of data on motion analysis with visualization. The third area of application that is explored is elderly patient condition monitoring and motion analysis for health monitoring.**

I. Introduction

Motion Analysis is an important area of research for many application domains. Various parameters can be assessed using motion of moving object for performance, efficiency and deterioration in the case of machines. Study conducted by Zetu et al [34] provides details about time and motion analysis to improve the process performance and adds efficiency by optimizing the actions of process workers. In the case of similar research by Balteanu [2], it is conducted for training factory workers to apply safe work practices while handling heavy loads. For Humm et al [13], Wang [27] and Fitzgerald [9], motion analysis is performed for biomechanical, sports and rehabilitation purposes. Research conducted by Ghandi [10] it applies computer vision for pedestrian collision avoidance. All these studies and research aspects assess overall motion analysis using computer vision which becomes very expensive in terms of memory consumption and processing speed. Lin et al [14] and Gandhi [35] take further approaches to reduce memory consumption and enhance speed using WSNs for similar applications. A major drawback noticed in this case was visualization of analysis was limited due to sensory limitations.

Another drawback of adhering to a particular paradigm is that it provides only sensor specific parameter details. This is enhanced with the tracking application by Xu [32], and with fusion of different sensors provides overall and detailed data of motion and adds additional information contents. This application has similar drawbacks as purely computer-vision based applications, but the advantage is that it can assess both low frequency and high frequency signals. Enhancing the performance advantages further, we propose a similar approach with an evolutionary computational algorithm. The application of an evolutionary computational approach reduces memory consumption and enhances speed. The second section discusses previous research conducted in same domain with similar approaches with their performances. In section three we discuss the proposed solution with system approach and algorithm. Section four explains the details of experiment conducted to prove the proposed algorithmic work. Further sections discuss the conclusion and future direction respectively. In essence, the potential of SANETs can be viewed beyond the domain of patient management systems, by demonstrating how a SANET environment combined with image recognition can enhance augmented reality methodologies in health care.

II. Background and Previous Works

A. Computer Vision for Motion Tracking and Analysis

The application of computer vision for feature tracking is one of the popular research areas for researchers. In this type of research area, the feature tracking can be performed using *Template Matching* or *Extraction and Matching* techniques. Template matching techniques include Correlation matching and Lucas-Kanade tracker (KLT). In the case of Correlation tracking [33], object movement with respect to its initial co-ordinates is tracked by using a spatial relationship between image frames periodically. The Luscas-Kanade Tracker [3] is a further modification of Correlation tracking. In this case, pixel movement of object in X and Y axis direction is summed to find actual overall object movement. Further work by Lowe [5] and Liu [21] proves very important to enhance motion tracking capability in terms of performance, but sensitivity towards scale and rotation makes Azad [1] a more attractive option. This image work focuses on Scale and Rotation invariant features to track object motion.

B. *Wireless Sensor Network for Motion Tracking Process*

The detection of motion analysis of a specific subject, especially with WSNs, is important in managing the routing and clustering mechanisms in a dynamic and volatile environment [1]. Unlike static wired networks, the reliability and guarantees on communication stability can never be assured. Furthermore, the dependency on nodes to follow through on message relaying means that the failure of one node may lead to an entire branch losing total connectivity. Another main aspect is security, as the network security can be prone to denial-of-service attacks or technological espionage like packet sniffing. These particular domain concerns, among others which are inherent with wireless networking, require the wireless network structure to adapt to changing environmental concerns to ensure the network's continual stability and robustness [24]. The following algorithmic categories are considered for an adaptive video-based WSN environment which suits the task for visual monitoring of healthcare:

- **Feature Mapping**
  By using a Self-Organising Feature Map (SOM) proposed by Kohonen [16], such as the Extended Kohonen Map (EKM) [25], the map self-organises to partition continuous sensory space into discrete regions. The feature map's generalisation capability arises from its self-organisation during training [17], such as when every node in the WSN is effectively trained to map a localised sensor region. This approach increases the sensory representation's resolution in the frequently encountered stimuli regions [20]. This conduct reflects biological sensory perceptions where frequent practice leads to better predictive capability of common, anticipated events.
- **Multivariate Regression**
  An alternative approach formulates the statement task as a non-linear multi-variate regression problem. Uninterrupted mapping from U to C is done by training a multilayer perceptron (MLP), which offers possible generalisation capability [24][28][30]. The main disadvantage prior to training the network is that training samples must be collected for each time step 't' to define quantitative error signals. As this sampling process is tedious and computationally difficult, it is solved with the reinforcement learning approach by providing a qualitative success or failure feedback at the end of the executing control sequence [15].

We propose an alternate feature map approach to be used for wireless sensor network governance concerns, through co-operative EKMs with indirect mapping [18]. This ensures that the sweeping of field vision as the subject is tracked across rooms and localities is done in a smooth, graduated manner. An indirect-mapping EKM approach is dissimilar to direct-mapping methods in the following techniques [25]:

- Direct-mapping methods map a sensory input directly to sensory stimuli for a node in the wireless network. Comparatively, the indirect-mapping approach maps sensory stimuli indirectly to a node clustering or routing directive with the utilisation of control parameters.
- Indirect-mapping approaches map the continuous sensory stimuli space to the node clustering or routing directive as an end result. Direct-mapping methods map the continuous sensory stimuli space to discrete clustering or routing directives for each node, as seen from a different perspective.

C. *Computer Vision & WSN for Motion Tracking Analysis*

Not many researchers have combined these two paradigms so far. In case of Desai et al [7], [6], wireless sensors are used for measuring tilt and pan of a camera used to track objects. In this case, actual tracking is performed by camera and listener motes. Cricket motes used in this work are capable to sense position and orientation of an object. This work provides very useful background knowledge to the work proposed in this paper. In this case, data fusion of Sensor Networks with Computer Vision is performed by using neural activation techniques. Thus, the fusion of these two paradigms gives valuable results and augments the level of image detail.

D. *Wireless Vision Sensor Network for Motion Tracking*

This is a relatively new area of research where concept of wireless sensors and camera vision is fused together as a Wireless Vision Sensor Network (WVSN) [26]. In this research domain combination of data from multiple low resolution cameras called Camera Sensors is fused together to build a motion profile. In case of Monari [23] agent based distributed software architecture system is proposed to track objects across multiple low resolution wireless camera sensors [4]. Proposes another middleware based solution using WVSN form tracking object motion by combining WVSN and Wireless Sensor Network. Research carried out by Hengstler et al [12], Shaw [29] and Wu et al [31] provides further details on applications related with WVSN for tracking and motion analysis.

Thus depending on scenario and available computational a particular strategy can be applied for tracking objects. In this paper we propose combined approach using Wireless Sensor Network and Computer Vision for tracking objects. This approach provides particularly good results in case of Surveillance applications. In such applications various issues which cannot be taken care using any of approach alone can be covered using combined approach. Especially occluded objects can be located or their presence can be sensed using this approach. In conjunction with a meta-heuristic model solution, SOM or EKM in vision monitoring is established and documented by [24]. However, the inconsequential problem of combining multiple SOMs or EKMs for sophisticated system control is a potential area of study. If the sensory control is insufficiently clarified, the routing or clustering decision made by a wireless node may be unexpected or undesirable, leading to a potential 'deadlock' to navigate a safe passage to the sink or wireless gateway [18], [22]. When SOMs or EKMs are established in the weighted-sum ensemble, a similar problem of deadlock also takes place.

To solve this deadlock problem, the combinational approach with co-operative EKMs will be applied to wireless sensor networks [18]. The co-operation and competition of multiple EKMs that similarly self-organise can enable a non-holonomic wireless node to optimise its routing and clustering choices in unexpected changes in its environment. In contrast, a node managed by the weighted-sum ensemble method will approach a routing deadlock, even though the wireless network also implements a continuous sensory control space. The governance directives given to a node in a wireless sensor network's control space is formed as a discrete set of commands to be used by reinforcement learning algorithms [25][22], or at the minimum level, pre-defined static rules. In recent years, autonomous agent research in dynamic systems theory and reinforcement learning propose the operation of such directives in a continuous control space [22], to allow the indirect-mapping method to provide finer directive decisions than in direct mapping. Focussing on the flexibility and precision in sensory stimuli control is imperative in a wireless network domain where external environmental factors directly affect the network's robustness and reliability.

Preliminary results demonstrate indirect mapping with EKMs provide an economical control and feedback mechanism by operating in a continuous sensory control space when compared with direct mapping techniques. By training the control parameter, a faster convergence is made with processes such as the recursive least squares method. The management of a WSN's clustering and routing procedures are enhanced by the co-operation of multiple self-organising EKMs to adapt to actively changing conditions in the video monitoring environment. The environmental concern, such as sensory stimuli, for a given wireless network domain can be summarised in the statement tasks [19]:

- For an initial state described by the input vector u(0) in input space U;
- Adapt new clustering or routing sequence of control vectors c(t), t = 0, ... , T−1, in the motor control space C;
- With the resultant goal state elaborated by u(T) ∈ U that adapts the network structure for a desired objective or target state.
- Calculated the Integration Matrix to determine and initialise the control matrix;
- Respond to change in the subject by activating the embedded cameras near the vicinity of the subject.

E. *Research Case Studies for Experimental Work*

The following Motion Analysis and Patient Tracking case studies will be examined for future experimental work:

- Tracking patients in environment in motion helps to find their motion pattern during rehabilitation. Generally during the rehabilitation period, the patient does not need strict hospitalization or bed rest. In such situations, especially when recovery demands specific motion patterns, it is essential to restrict body movements within accepted threshold levels (to not behave too energetically).
- An alternative situation can be considered for treatment due to post-rehabilitative care (i.e. sports injury), then motion pattern can be used for analyzing treatment and patient response analysis.
- Performance evaluation applicability can be used for preventative measures against sports or body-mechanic related injuries. Here, a macro-level analysis of gait and other body stresses are done by camera vision and micro-level by active sensors.

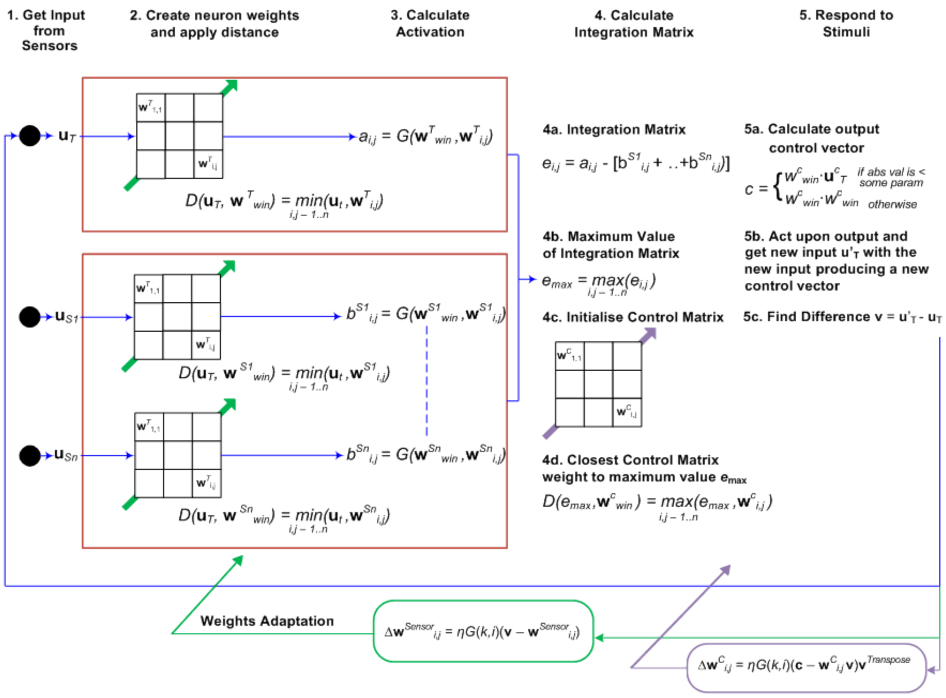

Figure 1: Self-Organizing EKM Wireless Video Sensor Network Designed in Combination with GA Heuristics [18]

III. METHODOLOGY

A. Problem Formulation

In case of the simulation scenario, we apply 2D vision for tracking patients. As the CMOS camera image represents a matrix of intensities, the space captured can be scanned periodically for presence and motion of patients. In this case we decided to track patient based on the centroid value for an average built person with +20% or -20% of tolerance. In this case, tolerance was assumed for calculating people with various heights and physical dimensions. As a computer vision point of problem formulation, this includes a matrix of intensities with movement of various centroid values of human body profiles.

B. Proposed Algorithmic Methodology

In the proposed algorithm we apply Genetic Algorithms [8] for detecting position of centroid of a moving human body. Once the image is captured it is pre-processed and segmented to separate the human body from background. Afterwards, the image is binarized for the sake of simplicity in calculations. Detection process starts with creating population of random pixel co-ordinates. In this process all pixels with intensity equal to that of the background are eliminated. After population creation, a Region of Interest (ROI) equal to the height and width of a human body is created, assuming the population element as a centre. For every ROI, the centroid value of an object component is calculated and compared with fitness function. The Fitness function is purely a centroid value with ±20% tolerance:

- If the fit element is found than position of fit element it is recorded as initial position.
- If fit element is not found, crossover and mutation operation is performed to find a fit element.

Once the fit element is found, its position is recorded. Once the centroid position is detected then the same operation is performed after a maximum of 2 minutes. In case of multiple patients in a search space, the multiple local optima technique is applied to find multiple moving patients. In Figure 2: Algorithmic Methodology of Image Heuristic Process, the multi-heuristic solution of the abovementioned process is accomplished by utilising the strengths of Cooperative Extended Kohonen Maps and Genetic Algorithms. The sensor network environment is mapped with web-cameras embedded on an Ardunio platform, and communicating using the ZigBee protocol, while a CMOS camera is attached to the wireless nodes.

When a particular node is activated via the Self-Organising EKM, the GA Centroid algorithm is then activated by capturing the input image frame for the respective webcam-enabled wireless sensor, and the image packets are passed on the main server to be handled by the computer vision process. The final results are presented on the graphical user interface running on the main processing server.

IV. EXPERIMENTAL WORK

A. Simulation Assumptions

1) The Wireless Sensor Network Topology Assumptions

- The topology of the SANET healthcare monitoring network is three-dimensional, although altitude is restricted to a 2m height constraint. A single floor setup is considered in the current scenario (multi-story network structures is a future concern)
- All nodes are powered initially at 100% capacity at the start of the experiment. Energy dissipation is calculated using inverse square law.
- The event trajectory is not predefined, such that the beginning and end points are calculated randomly using Fast Mersenne-Twister method.
- The network is considered to be interference free; as such RF communication concerns or Quality of Service constraints are not evaluated in the model (i.e. the WSN operates on a best-effort basis).
- The current experimental setup assumes a 1:15 ratio of physical to virtual sensors (with physical sensors rounded-up), with a maximum of 16 physical sensors in the experimental setup.

2) Image Recognition Assumptions

- The video imaging setup is based on a QVGA resolution of approximately 320x240 pixels (100,000 pixels) at a colour depth of 16 bits.
- The recognition detection system utilises OpenCV in the Visual Studio C++ environment.
- Image Processing is performed externally on a server platform in tandem with the Jadex platform.

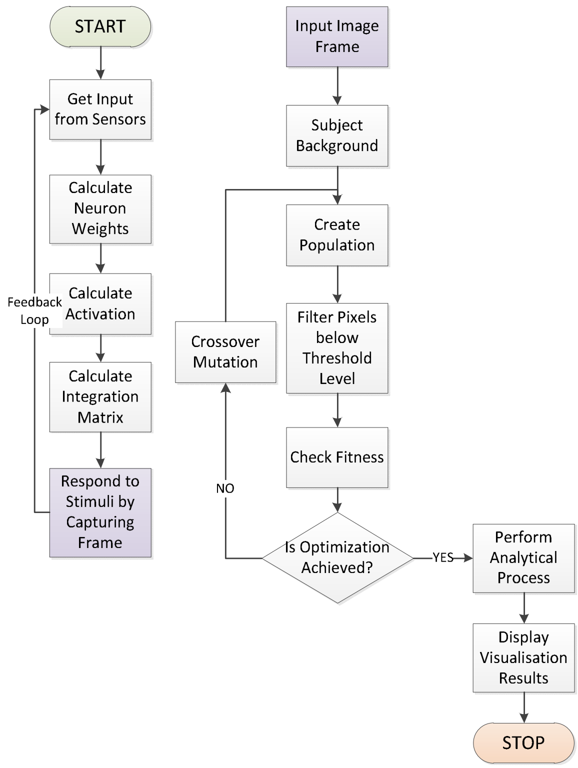

Figure 2: Algorithmic Methodology of Image Heuristic Process

B. Experimental Setup

The evaluation of co-operative EKMs with R-B optimization on SANETs is executed using the framework conceived by Chaczko, et al [30]. The Jadex framework by Universität Hamburg, shown in Figure 3 allows for convenient monitoring and tracking of SANET events by pre-assigning event trajectories in the network field in an interactive manner in the Java Runtime Environment.

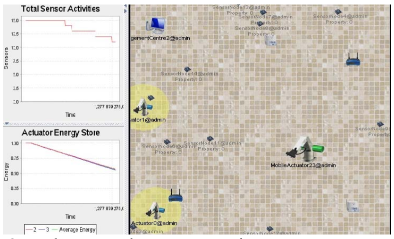

Figure 3: Jadex Development Environment screen-capture

C. Experimental Procedure

The experiment is completed with the methodology by establishing the following experimental constraints:

1. A population of n nodes is distributed randomly via Fast Mersenne-Twister, in a 3-dimensional network of 10m x 10m x 2m. Node populations tested include: 25, 50, 100, 200 and 250 nodes.
2. An event trajectory is executed from a point in the network area; of which the test path course is a:
    a. Linear Path: A linear path consists of an event trajectory where the entry and exit point from the area is of constant gradient.
    b. Arc-formation Path: Arc-formation consists of an event trajectory where entry and exit point will either be increasing or decreasing in gradient, forming a circle segment.
    c. Pseudo-random Path: A pseudo-random path using the Mersenne-Twister method combines 2(a) & 2(b) at various trajectory points, until it reaches the exit point.
3. The algorithm selects the route from the node in range of the approximate trajectory to be established to the sink; such that the closer the algorithm is to calculating event path, the more optimum the route.
    a. Co-operative EKMs with PSO: Co-operative EKMs use an indirect-mapping SOM map to train the control parameters in which to converge at the final trajectory point; in such a fashion to actively train the neural network to seek positive outcomes to determine a route from the trajectory's path to the sink.
    b. Co-operative EKMs with R-B Optimization: In conjunction with Co-operative EKMs, a filtrating mechanism is applied to the weights adaptation map using the Rao-Blackwell optimization to assist in event tracking.

    In conjunction, the reinforcement learning heuristic applied to the SOM map as a training vector set, and a vector test set is applied to maintain accuracy of path estimation. Using Particle Swarm Optimization [17], the shortest Euclidean distance between the specific trajectory point and the nearest neighbouring node is nominated within the routable path to the sink.
4. The experiment is executed for 100 iterations to calculate the mean rate of successful identification of the trajectory's target point:
    a. A maximum margin of error is a 2m x 2m area where final approximate point is found.
    b. A successful identification is where the final end-point is within a 95% confidence interval of the entire network. Any estimation outside of this threshold is a failed identification.

D. Experimental Results

The results demonstrate that in comparison to co-operative EKMs with PSO and Rao-Blackwell optimization, the final results are positive when pseudo-random trajectory tracking is required. While standard Co-operative EKMs perform adequately in the given scenarios; co-operative EKMs with Rao-Blackwell optimization demonstrates a perceptible improvement in the identification rate over standard co-operative EKM algorithms. This is evident with a greater node population, as the granularity of determining a nearest neighbouring node to route is reduced for the fixed size of the network. In Figure 4 there is a 40% relative improvement in the average mean detection rates with Rao-Blackwell optimization for the pseudo-random trajectory compared to standard co-operative EKMs. As co-operative EKM with R-B optimization demonstrate improvement over passive learning techniques, current prediction rates are sufficient for data routing estimation capability, which indicate the process of refining the training set for remodelling is necessary to improve the SANET vision routing condition.

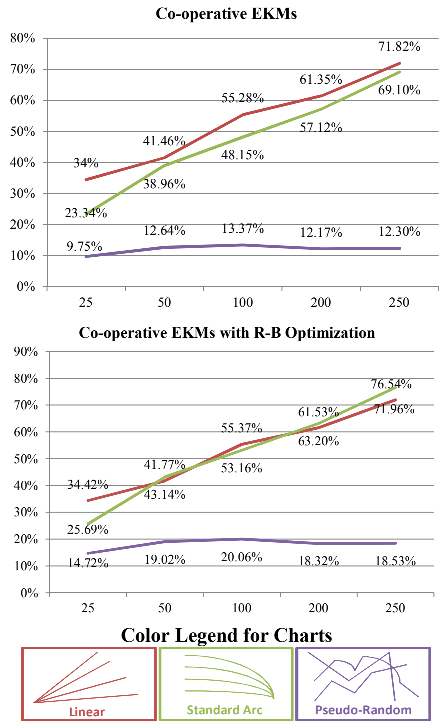

Figure 4: Experimental Results of Detection Success

The detection rates for the GA centroid algorithm are presented in the table below, where $A_d=(A_t-A_c)/A_t$ determines the area of the humanoid subject, while I_d is the absolute difference between the template and chromosome intensity. Performance considerations are not evaluated.

TABLE I
GA CENTROID ERROR RATES

Pixel Population Size	Fitness level	Error percentage
100000	$A_d = 0.10$, $I_d = 0.6$	4%
100000	$A_d = 0.10$, $I_d = 0.6$	4%
100000	$A_d = 0.10$, $I_d = 0.6$	3%
100000	$A_d = 0.10$, $I_d = 0.6$	2%

V. CONCLUSION

An innovative method of adaptive wireless sensor network governance responsibilities in fusion with vision recognition systems with co-operative EKMs has been established through evaluation; the preliminary results demonstrate indirect-mapping EKM generates more proficient wireless network governance decisions than other local learning methods like direct-mapping EKM. With recursive least squares, the control parameters of the indirect-mapping EKM can be trained to allow rapid convergence and improved optimisation when compared to the gradient descent.

VI. FUTURE DIRECTIONS

The Healthcare Motion Analysis System, through its design and demonstrative capability, provides an insight to facilitate an effective software environment for managing the needs of senior citizens in an aged-care environment. There is significant potential to integrate the system in an open-distributed middleware architecture, such that the health-care professionals can assess their patient monitoring strategies from a remote location in a video recognition context. In future, effective consultation with health care professionals, the video monitoring environment will implement more practical cases and scenarios common to patient health care management. This should provide a better understanding of the main concerns that lie ahead, in terms of research scope and encompassing the problem domain in the core concepts.

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