

Wireless Visual 3D Sensors For Monitoring Environments And Resource Allocation

Anto Rose. R^1 , Vinod. S^2 , Daya Florance. D^3

^{1,3}ME CSE, Vel Tech Multi Tech Engineering College, Avadi, Chennai. ²Asst Professor, Dept of Computer Science and Engineering, Vel Tech Multi Tech Engineering College, Avadi, Chennai.

Abstract— The Sensors plays vital role in many fields like monitoring volcano, fire etc. This paper investigates the resource allocation for each and every sensed data. In this we considered a single hop network topology. Each and every sensors in single-hop network topology transmit the sensed data directly to a centralized control unit(CCU), Which manages the available network resources. The normal sensors does not sense the environmental condition properly, so for sensing the environmental condition properly instead of normal sensors we consider 3D sensors. The Sensed data like the data which are in video format requires more quality. For providing quality we use various quality driven criteria, which provides more quality for the varying motion characteristics of each recorded video. The CCU provides transmission power and source channel coding rates for each nodes. The swarm optimization algorithm is used for monitoring dynamic nature of the environment, the approximation algorithm is used for solving the coverage problem and the greedy algorithm is used for covering the most region. The simulation is used for demonstrate the process.

Keywords—Centralized Control Unit, Dynamic Nature, High Quality,Video Motions, Resource Allocation, 3D Senors.

I. INTRODUCTION

Sensor is used for sensing the data it is used in many fields like Military, Volcano region, Medical field etc, There are various types of sensors are available for example rain sensor is used for sensing rain, then fire sensor is used for sensing fire and so on. Each and every sensors have battery without battery it will not work. Normal sensors sense only in one direction, it won't cover maximum region. If we want to cover the environment by normal sensors means we need more sensors, because of this the cost and the power consumption increases. For avoiding that in this paper we consider 3D sensors. The main advantage of the 3D sensor is to cover maximum region than the normal sensors.

Instead of normal sensors if we use 3D sensors means there is no need to use more sensors so the cost and the power consumption decreases. The sensors should transmit the sensed data to the Centralized Control Unit. For data transmission i.e, the sensed datas by sensors needs to transmit towards Centralized Control Unit for that it requires topology. Many topologies are available in this it uses single hop topology for data transmission. The 3D sensor sense the environmental condition accurately. The environmental condition is dynamic[4] so it is very difficult to capture the video of changing environment in high quality. Without quality the entire sensing data will be wasted.

In satellite also they are using more number of sensors for sensing the planets, oceans etc. Without quality we cannot able to predict the conditions of planets, oceans etc. For providing quality and preventing the sensed data without any loss is the main thing in sensors.

In this paper all the nodes share the same frequency ant then it will communicate to the centralized Control Unit(CCU). There are several kinds of cameras are used in the sensors for taking photos and capturing videos. The CCU uses the channel and the source encoding for receiving the video as high quality from the sensors. For receiving the high quality of video from sensors means each and every sensor[2] should have different resource requirements i.e source coding rate and delay coding rate.

The transmission of each node has on affect on other node due to interference. Because of the interference the quality of the video should get degrade. For avoiding the interference we have vary the packet data transmission timing between each and every nodes. The quality driven techic is used for improving the quality it allocates resource for each nodes. i.e., transmission power. In this two node grouping techic is used[6]. The priority is given to all nodes for reducing the packet loss and improving the quality of the video. The node which carry high quality video is to be given high priority. High motion videos are more sensitive to channel losses. Assuming a fixed budget for source and channel coding rate, less strong channel coding will have to be used for high motion videos[5]. The low motion videos can be encoded at a lower source coding rate.

This will leave more bits available for channel coding and will allow adequate transmission using a lower transmission power.



Higher priority compared to the low motion sensors, and hence achieve relatively higher delivered video quality.

II. ARCHITECTURE

The Architecture of the Wireless Visual Sensor Network consist of several nodes. The nodes are used for transmitting the data from source to the destination. The WVSN uses single hop topology and also it contains clusters, visual sensors and centralized control unit. The clustering visual sensor is used for reducing the computational complexity. In this paper we propose the clustering according to the individual video content–related parameters. As a result, each node becomes a member of a cluster represented by its centroid Fig[1]. The transmission parameters are allocated according to the centroids of the clusters. Based on those, we estimate the expected video quality of each node.

The visual sensor is used for sensing the environmental conditions. After sensing it transmit the data to the centralized control unit. In this paper we describe about the 3D sensors, so that it will cover all the environmental conditions properly

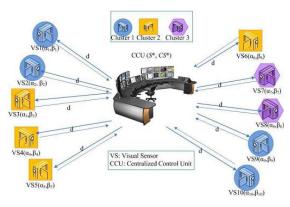


Fig 1: Visual Sensor

The above diagram shows the visual sensors anh how the transmission is taking place. Initially the visual sensors(3D) sensors transmitting the sensed data, this paper we are considering the sensed data as video's. After sensing the video it will transmit the video to the centralized control unit. While transmitting the data between node there may be a chance to packet loss. For avoiding the packet loss and the delay in this paper we are using resource allocation. The network's resource allocation can be heavily dependent on the video data "importance", as it is dictated by the corresponding application

The recordings of the cameras with high motion require a larger source coding rate than low motion videos. High motion videos are more sensitive to channel losses. Furthermore, assuming a fixed budget for source and channel coding rate, less strong channel coding will have to be used for high motion videos. On the other hand, low motion videos can be encoded at a lower source coding rate. This will leave more bits available for channel coding and will allow adequate transmission using a lower transmission power. Thus, the cameras capturing scenes of high motion have different requirements than cameras capturing scenes of low motion. Therefore, we use a prioritization scheme based on the amount of motion detected in a video sequence. According to it, visual sensors that record higher motion receive a proportionally higher priority compared to the low motion sensors, and hence achieve relatively higher delivered video quality.

Finally, in our work we achieve motion–related proportional video quality enhancement of the nodes. Particularly, we employ motion–related bargaining powers to formulate our NBS criterion. So far, the resource allocation methods of power and joint source-channel coding rate in video communication applications have not taken into consideration this requirement and formulation. Related work in video transmission has only considered the tradeoff of video quality and channel coding rate selection with regard to the video distortion impact.

A. 3D Sensors:

The 3D sensors are used for sensing the data in 3D view so this sensor is very useful for volcanic region, military purposes, hospital purposes etc.,

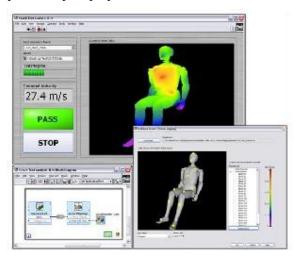


Fig 2: 3D sensor images.



The above image shows how the 3D sensor sensing the image accurately. The 3d sensor sense the image or the environmental conditions in 3D view it means the sensed data in accurate manner.

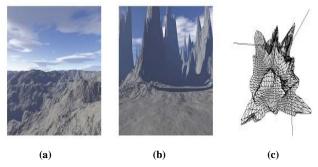


Fig 3: Surface coverage in 3D sensor

The Glaciation parameter is used to increase the coverage ratio. All sensors can be only deployed on the surface. In this simulation, the size of theFoIis set to be 1,920 m. The height range is from 300 mto2,000 m and the sensing radius is30 m. Finally, we calculate the coverage ratio. When Glaciation is 0.When the parameter Glaciation increases, the coverage ratio Glaciation is 60 decreases quickly.

B. Clustered WVSN nodes:

This approach is motivated by the need for effectively reducing the computational complexity. We propose the use of clustering according to the individual video content– related parameters. As a result, each node becomes a member of a cluster represented by its centroid. The transmission parameters are allocated according to thecentroids of the clusters. Based on those, we estimate the expected video quality of each node.

C. Solutions:

The WVSN node requirements to achieve higher video end-to-end quality, are conflicting. If the nodes behaved self-ishly, they would try to maximize their video quality regardless of the choices made by the other nodes. This would result in all nodes transmitting using the highest available transmission power, leading to excessive interference, and thus in quality degradation Therefore, we use the game theoretic Nash Bargaining Solution (NBS) to organize a bargaining game. This game refers to a conflict of interest situation in which the nodes agree to negotiate in order to conclude a mutually beneficial agreement.

D. Related Works:

The problem objective was to maximize the network throughput, which does not necessarily lead to the maximum possible video quality at the receiver. Moreover, assuming similar rate-distortion curves in adjacent time slots does not result in good quality for the cases where a sudden change in the captured motion level occurs. Opposed to that, our proposed update mechanism effectively addresses low to high changes in the rate distortion curves and quickly re allocates the network resources. The end-to-end video distortion with the motivation to depict the quality impact of he resource allocation. Besides that, an algorithm to determine the bargaining powers according to the allocated bit rate per user. The resource allocation methods of power and joint source-channel coding rate in video communication applications have not taken into consideration this requirement and formulation. Related work in video transmission has only considered the trade off of video quality and channel coding rate selection with regard to the video distortion impact.

F. Contribution and Structure of the Paper:

The efficiently allocate the network resources of a DS– CDMA WVSN taking into consideration the individual rate–distortion characteristics of each node. This paper concentrate their work towards many applications.

(a) Investigating the quality, power and complexity tradeoffs:

In this we compare the complexity, power and trade offs. The first one allocates the resources individually for each sensor according to its individual rate–distortion characteristics, while the second clusters them according to the recorded level of motion and allocates the same resource.

(b) Motion-related prioritization of nodes using game theory:

The recordings of the high motion cameras are susceptible to channel errors, thus reach the CCU with low quality, opposed to the low motion videos which are more robust. It is therefore sensible that cameras capturing scenes of high motion have different requirements. So far, the resource allocation methods in video communication applications have not taken into consideration this requirement.



Therefore, we provide a simple yet effective game theoretic motion related prioritization of the network resources and enhance the end-to-end video quality of the high motion nodes. Furthermore, our approach demonstrates the advantage of computing locally at each node (not at the CCU) the motion characteristics of each recorded video.

(c) Dynamically changing environment:

Dynamic environment with variations in the amount of motion in the recorded scenes through time. For this reason, we introduce two PSO–based algorithms for the re– allocation of resources after each change in the environment.

$$R_k = \frac{R_{\mathrm{chip},k}}{L},$$

The L chips are transmitted by a node. Each node is associated with a spreading code.

G. Algorithms:

We propose many algorithms for various purposes like resource allocation.etc.,

(a)Source Coding:

The source coding of the captured video sequences, the H.264/AVC video coding standard is used. The H.264/AVC design consists of two conceptual layers: the Network Abstraction Layer (NAL) and the Video Coding Layer(VCL). The NAL, which was created to fulfil the network-friendly design objective, formats data and provides header information for conveyance by transport layers or storage media. All data are encapsulated in NAL units, each of which contains an integer number of bytes. The NAL unit structure provides a generic form for use in both packet-oriented and bitstream- based systems. The format of NAL units is identical in both environments, except that each NAL unit is preceded by a unique start code prefix for re-synchronization in bitstream- oriented transport systems. The VCL is specified to efficiently represent the content of the video data and fulfill the design objective of enhanced coding efficiency. It is similar in spirit to designs found in other standards in the sense that it consistsof a hybrid of block-based temporal and spatial prediction in conjunction with scalar-quantized block transform coding.

Algorithm 1 Pseudocode for Computing Parameters (α, β) at Each Node *k*

- 1: for three different P_{be} do
- 2: for each frame m do
- 3: for each pixel p do
- 4: Estimate $E[D_{s+c,k}^p]$ according to the ROPE algorithm [23].
- 5: end for
- 6: Estimate $E[D^m_{s+c,k}] = \frac{1}{\# \text{ of pixels}} \sum_p E[D^p_{s+c,k}]$ for frame m.
- 7: end for
- 8: Estimate the Mean $E[D_{s+c,k}]$ for the video sequence.
- 9: end for
- Use Least Squares to estimate (α_k, β_k) from the pairs of (E[D_{s+c,k}], P_{be,k}).

Algorithm 1 details how we determine the values of para-meters α k and β k for each node at the encoder. For the accurate estimation of thedecoder distortionE[Ds+c,k] at the encoder, the Recursive Optimal per-Pixel Estimate(ROPE) algorithm is used. The ROPE algorithm recursively cal-culates the first and second moments of the decoder recon-struction of each pixel E[Dps+c,k], while it accurately takes into account all relevant factors, i.e. quantization, packet loss, error propagation and error concealment. Due to the fact that ROPE uses the Packet Loss Rate(PLR) to compute the overall expected MSE distortion of a pixel.

(b) Employed optimization algorithms:

The Particle Swarm Optimization (PSO) algorithm served as our optimizer in all cases. PSO belongs to the category Swarm Intelligence methods, which draw inspiration from the collective intelligence that emerges in physical systems of living organisms.



The use of PSO does not require convexity of the problem or the constructions of hierarchies of (mixedinteger) convex relaxations and the approximation of the problem's nonlinearities with convex under- and concave over estimators (i.e., the convex and concave envelopes of the objective function). This can be particularly useful in practical situations.

Algorithm 2 Pseudocode of PSO-PS

- **Require:** Previous and current parameters $\alpha_{k,t-1}, \alpha_{k,t}$ and $\beta_{k,t-1}, \beta_{k,t}$ for each node k, previous resource allocation $(CS^*, S^*)_{t-1}$, parameter α_k variation threshold δ_{α} .
- 1: **loop**
- 2: if any $|\alpha_{k,t-1} \alpha_{k,t}| > \delta_{\alpha}$ then
- 3: Run the clustering algorithm to form the new clusters. /* Only for Clustered WVSN nodes */
- 4: Initialize half of the swarm around the previous allocation $(CS^*, S^*)_{t-1}$.
- 5: Initialize the other half of the swarm in random positions within the predefined ranges.
- 6: Run the PSO update function.
- 7: Send to the nodes the updated resource allocation $(CS^*, S^*)_t$.
- 8: end if
- 9: end loop

where, i = 1, 2, ..., N; j = 1, 2, ..., n; the parameter χ is the constriction coefficient; acceleration constants c1 andc2 are called the cognitive and social parameter, respectively; and R1, R2, are random variables uniformly distributed in the range [0,1]. It shall be noted that a different value of R1 and R2 is sampled for each i and j. Also, the best position of each particle is updated at each iteration, as follows:

$$p_i(t+1) = \begin{cases} x_i(t+1), & \text{if } \mathcal{F}(x_i(t+1)) < \mathcal{F}(p_i(t)), \\ p_i(t), & \text{otherwise} \end{cases} \in I$$

Based on its stability analysis, the parameter set $\chi=0.729$, c1 = c2 = 2.05, was determined as a satisfactory setting that produces a balanced convergence speed of the algorithm.

(C). Greedy algorithm for solving coverage problem:

Input : Partition \mathcal{P} , function h of every pieces S_i Output: A subset \mathcal{P}' of \mathcal{P} $\mathcal{P}' \leftarrow \emptyset$; $\mathcal{C} \leftarrow \emptyset$; while $\mathcal{C} \not\supseteq \mathcal{P}$ do $\left|\begin{array}{c} m \leftarrow 0, x \leftarrow 0; \\ \text{for every } S_i \text{ in } \mathcal{P} - \mathcal{P}' \text{ do} \\ | \text{ if } |h(S_i) - \mathcal{C}| > m \text{ then} \\ | m \leftarrow |h(S_i) - \mathcal{C}|; x \leftarrow i; \\ | \text{ end} \\ end \\ \mathcal{P}' \leftarrow \mathcal{P}' \cup \{S_x\}; \ \mathcal{C} \leftarrow \mathcal{C} \cup h(S_x); \\ end \end{array}\right|$

These strips are then considered in groups of consecutive strips resulting in strips of width D each. For any fixed division into strips of width D, there are 1 different ways of partitioning FoI into strips of width D. These partitions can be ordered such that each can be derived from the previous one by shifting it to the right over distance D. We use the same method to solve the sub problem and output the union of all positions. For 1 different shifting partitions.

H. Simulations:

The Simulation shows the realistic output of our experiment.

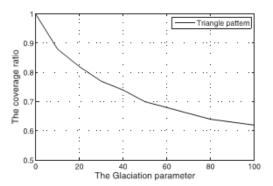


Fig 4: Covering surface using glaciation parameter



The number of sensors is set to satisfy the minimum value for achieving full coverage (the coverage ratio is 1) when Glaciation=0.When theparamete Glaciation increases, the coverage ratio decreases quickly. It drops to about 60 percent whenGlaciation=100. Hence, the conventional triangle pattern does not work well on a complex surface. It is necessary to find new methods to cover the complex surface.

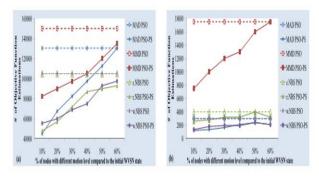


Fig:5 Nodes with different motion level.

The number of objective function evaluations has an increasing tendency as the percentage of nodes with different motion level from the initial levels increases. On the contrary, for TC2 the number of objective function evaluations using PSO–PS demonstrates a smoother increasing tendency, and in some cases remains the same or slightly decreases.

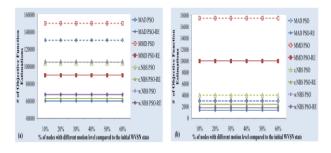


Fig:6 Nodes Comparision

PSO–PS initializes the swarm around the prior solution, which was computed based on the initial αk values, and does not result in a constant maximum number of objective function evaluations. Opposed to this, PSO–RE performs the rough estimation of the transmitted power based on the current time instance αk values.

Hence, it locates the swarm close to the optimal solution, and it converges after a small and constant maximum number of function evaluations every time there is a change of motion in thescenery for all the criteria and test cases, as observed in [Fig. 6].Furthermore, similarly to PSO–PS, TC2 converges faster than TC1.

PSO–RE ensures a constant and low maximum number of objective function evaluations, which is of great importance especially for real–time applications.

III. CONCLUSION

We have used 3D sensors for sensing the environmental situations. For surface covering in 3D we use Greedy algorithm. The Greedy algorithm solves the coverage problem. Then we allocate the resource for the sensed video, the resource allocation prevents the sensed video from packet loss and also we used some efficient algorithms like particle swam optimization algorithm for improving the video quality.

A fixed budget for source and channel coding rate, less strong channel coding will have to be used for high motion videos. On the other hand, low motion videos can be encoded at a lower source coding rate. This will leave more bits available for channel coding and will allow adequate transmission using a lower transmission power. Thus, cameras capturing scenes of high motion have different requirements than cameras capturing scenes of low motion we use a prioritization scheme based on the amount of motion detected in a video sequence. According to it, visual sensors that record higher motion receive a proportionally higher priority compared to the low motion sensors, and hence achieve relatively higher delivered video quality.

REFERENCES

- I. F. Akyildiz, T. Melodia, and K. R. Chowdhury, "A survey on wireless multimedia sensor networks,"Comput. Netw. J., vol. 51, pp. 921–960,
- [2] S. Soro and W. Heinzelman, "A survey of visual sensor networks," Adv.Multimedia, vol. 2009, pp. 640386-1–640386-21, May 2009.
- [3] Y.-C. Lin and S.-C. Tai, "Fast full-search block-matching algorithm for motion-compensated video compression," IEEE Trans. Commun., vol. 45, no. 5, pp. 527–530, May 1997.
- [4] E. S. Bentley, L. P. Kondi, J. D. Matyjas, M. J. Medley, and B. W. Suter, "Spread spectrum visual sensor networks resource management using an end-to-end cross layer design,"IEEE Trans. Multimedia, vol. 13, no. 1, pp. 125–131, Feb. 2011.
- [5] Y. S. Chan and J. W. Modestino, "A joint source coding-power control approach for video transmission over CDMA networks," IEEE J. Sel. Areas Commun., vol. 21, no. 10, pp. 1516–1525, Dec. 2003.



- [6] M. Cardei, M. Thai, Y. Li, and W. Wu, "Energy-Efficient Target Coverage in Wireless Sensor Networks,"Proc. IEEE INFOCOM,vol. 3, pp. 1976-1984, Mar. 2005.
- [7] M. Jin, G. Rong, H. Wu, L. Shuai, and X. Guo, "Optimal Surface Deployment Problem in Wireless Sensor Networks,"Proc. IEEE INFOCOM,pp. 2345-2353, 2012.
- [8] S. Kumar, T.H. Lai, and A. Arora, "Barrier Coverage with Wireless Sensors,"Proc. ACM MobiCom,pp. 284-298, 2005 X.-Y. Li, P.-J. Wan, and O. Frieder, "Coverage in Wireless Ad Hoc Sensor Networks,"IEEE Trans. Computers,vol. 52, no. 6, pp. 753-763, June 2003.