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Smart Dust Network for Tactical Border Surveillance System

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Abstract: ***Smart dust is nothing but the sensing element which is used to sense any light signal, heat, etc. Sensing is simply a identifier, i.e., to find whether anything or anybody available in our location or not. Nowadays this smart dust is used as tiny bits in Wireless Sensor Networks (WSN) to monitor the nodes present anywhere. One of the applications is that to effective in watching/ supervising border (secretly recording/ watching people) applications. When the positions of the tiny bits are subject to external forces, data from the WSN are only useful when combined with individual tiny bit. This problem can be avoided by a set of instruction related to things slowly changing for the better over time; which uses 'geometric-awareness' operators that hold back the positions a WSN tiny bit can occupy to those that have a better chance of maximally adding/ giving to the chromosome fitness. A combination of two things/gas-electric vehicle containing/ making up the specialised and standard operators is also tested. This way increasing the chances for doable/ possible WSN applications developed, and fielded a wireless sensor network that demonstrated the value of providing advanced information of adversary activities. The project used wireless technologies to detect and test/evaluate intruders in remote bit "un- designed and made" terrain around a fixed facility. In the time since the wireless invasion detection system was fielded, minimal time has been spent on maintenance and no batteries required replacement.Wireless sensor network provides advanced warning of intruder activities and its installation will improve the security way of standing/ attitude of a facility.***

Keywords: Smart dust, evolutionary algorithms, environmental monitoring, location estimation, heuristically directed evolution, geometric-awareness.

1. Background

Recent enduring Wireless Sensor Networks (WSN) installations in [4, 5, 6] are all provide work for static configurations. This paper apprehensive with applications, in which the relative locations of motes can change speedily, where there is a requirement to preserve a documentation of their locations, so that the data collected can be correctly interpreted. Certainly, the Global Positioning System (GPS) [7, 8] gives a convenient result to WSN localisation, however GPS has two main disadvantages; it needs a good vision of the sky which restricts its use to the outside environment; secondly the size, cost, power constraint and general operational practicality are momentous restrictions. This paper employ a computer form of a WSN of 'Smart Dust' (SD) motes envisioned as 'free-flying' in a 3-Dimensional airspace. The motes generate, without any human intervention, Relative Signal Strength Indicator (RSSI) [9] data aselement of the data packet stream consequently stored asstructured datasets by a gateway module. The SD module worn for the gateway to the 'outside-world' correspond to the only fixed reference point. Determining the position of each mote in such a WSN network is considered as a significant problem. This paper is used to approach this problem by applying some of the optimisation techniques. This paper investigates the use of Evolutionary Algorithms (EA)as the processing engine to produce candidate geometric positional cluster solutions depends on the implicit relative constituent positional geometry 'encoded' in the RSSI input datasets. The paper [10] resolute that a simple EA was competent of exact results for relatively small networks, it out performed hill climbing and random search for problems with morethan 20 motes. The paper [3] attempt to progress the problem faced that can be addressed, and speed up the process, by examining intelligent operators that apply restriction to the set of locations that any mote can occupy.

The results of the paper[3] are cheering; with much prospective erudition possible and it is possible to develop performance. It is clear from this paper that small clustersizes can be get to the bottom of efficiently, and very resourcefully by the model, especially with the intelligent-operators EA. The performance on P5-20 is also compared with the performance of the hill climber as reported in [10]. The EA model established good performance in spite of the size of the problem, as all research sizes (P5 to P100) shows the results that were, possibly, tolerably close to the ideal to be useful as data input for further processing. In other words, these results produced in [3] recommend that' dynamic' smart-dust data gathering applications, such as determining interior aspects of clouds (but there are many others) are practicable for modest numbers (5 to 100)of motes.

A clear restriction of the work presented in [3] is that anybody can use error-free datasets. In tradition, datasets will have errors happening from lost or contaminated RSSI packets. Exemplifying errors realistically is the topic of interesting research work, and this paper [3] have already researched with simple error models (using lost packet errors) that show a elegant deprivation in performance as error rates move from 0 to 20%. It is unclear to what extent the dreadful conditions will make a differentiation in feasibility of certain applications.

However, this paper took this as an interesting research work that this paper expect to deal with realistic errors in two traditions: first, operators (and fitness) are incorporated a good error correction model, secondly: the dynamic environment in which this real world problem needs to be

solved typically involve a *series* of localization problems at different time stamps – the series of solutions to these problems clearly constrain each other, providing extra information by which we expect to counterbalance some of the effect of errors. Meanwhile, we note that a further limitation of the EA model is its speed, which means at present we are considering only applications in which localisation data can be constructed offline following the data gathering process (with data recorded via the gateway).

In addition to commerce with data errors, this paper contains more intelligent operators which apply restrictions over *clusters* of motes; for example, if a mote is moved towards a meticulous spherical boundary, supplementary mutations will be prepared to conserve that mote's geometric relationship with a subset of others.

Also the second part of the paper is target classification, which is a significant enabling technology for the supervising task in transportation sensing networks. The paper [2] uses the magnetic signal and seismic acceleration signal which are collected, analyzed and transmitted for a mobile road target. A classification algorithm based on the sensor network is proposed, which adopts a peak and valley pattern of mixture recognition signals from dissimilar sensors. The hardware tools of the system of sensor node are formulated. The terminal nodes are tiny with little power utilization so that the transportation sensing network is simple to install. The advantage of this algorithm smears on its sorting accuracy of several types of targets. The results from many field tests have been exposed that it is talented of recognizing mobile targets on some roads in intelligent transportation system.

2. Model Overview

This paper is used to monitor the tactical border surveillance system using Smart Dust Technology. This paper presents a model to monitor the border surveillance system which consists of two major part, namely target locating system and target classification system.

2.1 Target Locating System:

This paper models the position estimation problem as follows. First defining the term input datasets that strictly bear a resemblance to the time stamped computer network packet data generally used in organization intranets. The payload, or time dependent data, enclosed in the packet is the computer-generated RSSI value between two known motes at a definite point in time. Initially, this paper employs the noise-free case, to launch a performance yardstick to establish the basic restrictions of the optimisation methods in the EA model. In this idealised state of affairs, this paper recall distances directly from the RSSI data, and hence it launch whether, and how speedily, correct relative 3D positions can be plagiaristic from these data by optimisation. This also shows the consequence the number of motes WSN has on the model performance. The chromosome is defined to be a set of relative WSN mote locations veiled as a vector of n 3Dcircumscribed co-ordinate triples, one for each building block in the WSN. This frankly symbolized the set of XYZ mote locations that comprise the current geometric elucidation as one part of the population. This paper also defines a minimising fitness function that is the similar for all research. The fitness value is the addition of all mean squared errors of the relative Euclidean difference magnitudes between the 3-Dimensionalpoints defining each mote pair; when they are all in the accurate location the error will be zero. It works by first manipulating a 'local-fitness' between each mote and all of its neighbours. The local-fitness is intended as the square of the difference magnitudes between two Euclidean distances, that of the current distance between a pair of (unique) motes with the equivalent RSSI values from the input dataset; this is repetitive for all motes. The local fitness is a valuable intermediate value that will be worn as piece of error rectification research.

Operators

Yardstick mutation and crossover operators (improved versions of those in [9]) are worn for the 'base EA' in this paper. Mutation operators modify the location of the motes by frankly and accidentally modifying the XYZ coordinates. Crossover is 'standard' uniform crossover. This paper launches a novel set of operators that limit the location that any mote can inhabit (errors not withstanding) in such a way that defined distance restrictions are maintained. In particular, the RSSI data point out (for a given timestamp) a distance between the reference (gateway) mote and a given mote m. When we mutate m's location, its new location is moved in the direction of the spherical surface defined by this radial distance. This drastically diminishes the search space. Idealistically, it might be likely to occur this would greatly raise the speed of finding good overall solutions. However, it is also wholly possible that local minima are just as widespread in this restricted space.

The pseudocode below illustrates theaction of these intelligent operators:

IF(constraint_distance**VALID**)
Calccurrent_distance to **REF** point for current mote
IF(within_constraint_range) **(S*tage 3)***
Move Mote =>***Maintain constraint_distance***
ELSE IF(within_single_step_range) ***(Stage 2)***
Move Mote =>***Withinconstraint_distance***
ELSE ***(Stage 1)***
IF(current_distance<constraint_distance)
Move Mote =>***INC_POSITION***
ELSE
Move Mote =>***DEC_POSITION***
ENDIF
ELSE Move Mote =>***Random*** (Std mutation operator)
ENDIF

Classification algorithm model for transportation targets:

Threshold design

The threshold of recognized signal is resolute by thesensing output voltage from the subsequent sensor. Aexhaustive threshold is determined by a lot of research.Here the threshold design method is set by:

$$threshold = \left|\frac{wavy\ value - base\ value}{the\ number\ of\ interval\ points}\right|$$

where the wavy value is an output voltage collected by asensor node with intrusion as no target overtake by. The

base value is the recognition data in a condition with neither mobile target nor intrusion. The base value would be wide-ranging with dissimilar roads and places. The number of interval points is the number of data between wavy value and base value. It is often bigger than or equals 2.

Transform method of peak value

The peak transformation pattern is a procedure that characteristic signals created by a target are altered into triple symbols {+1, 0, -1}, where the key character for acknowledgment is obtained. This process has a very high compress ratio such that the concurrent taxonomy has a less working out cost and low energy utilization.

Construction of sample base:

By using peak transformation pattern, all silky signals composed by a sensor node are altered into peak and valley style. A sample base can be built for detection algorithm in the course of much research.

Target pattern recognition method:

As a target is tested for detection with its sampling signals, the character set is contrasted with the recognition signals. It is calculated as:

$$R = |c_1 - c_{b1}| + |c_2 - c_{b2}| + \dots\dots\dots + |c_{10} - c_{b10}|$$

Where $\{c_1, c_2, \dots, c_{10}\}$is a vector of peak values, and$\{c_{b1}, c_{b2}, \dots, c_{b10}\}$is the produced character set of sample.

3. Result and Discussions

The various results obtained at this research as follow:

Threshold design

The classification model is designed as follows.

Table 1: An example of signal data collected by magnetic sensor

Output signal (mv)	Sampling time
64	15:26:48
64	15:26:48
64	15:26:49
64	15:26:49
63	15:26:49
63	15:26:49
64	15:26:49
64	15:26:49
64	15:26:49

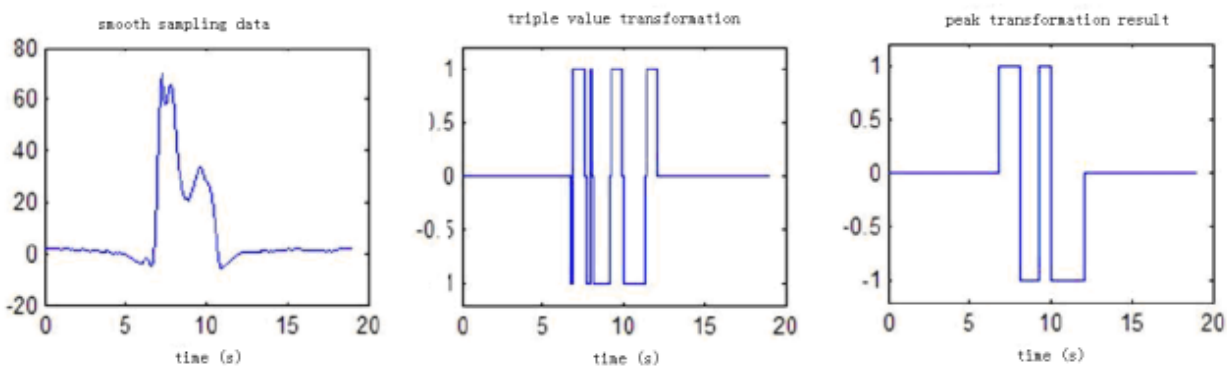

Figure 1: An example of peak transformation process

Table 2: Magnetic and seismic sample character set for target classification

Target type	Magnetic symbol vector	Seismic symbol vector
Free personnel	{0,0,0,0,0,0,0,0,0,0}	{+1,-1,0,+1,-1,0,+1,-1,0,+1} or {-1,+1,0,-1,+1,0,-1,+1,0,-1}
Personnel with mental object	{+1,0,-1,+1,-1,0,0,0,0,0}	
Small vehicle	{+1,-1,0,0,0,0,0,0,0,0}	{+1,-1,+1,-1,+1,0,0,0,0,0} or {-1,+1,-1,+1,-1,0,0,0,0,0}
Passenger car	{-1,+1,-1,+1,-1,0,0,0,0,0}	
Heavy vehicle	{+1,-1,+1,-1,0,-1,0,0,0,0}	
Tracklayer	{-1,+1,-1,0,0,0,0,0,0,0}	{+1,-1,+1,-1,+1,-1,+1,-1,+1,-1} or {-1,+1,-1,+1,-1,+1,-1,+1,-1,+1}

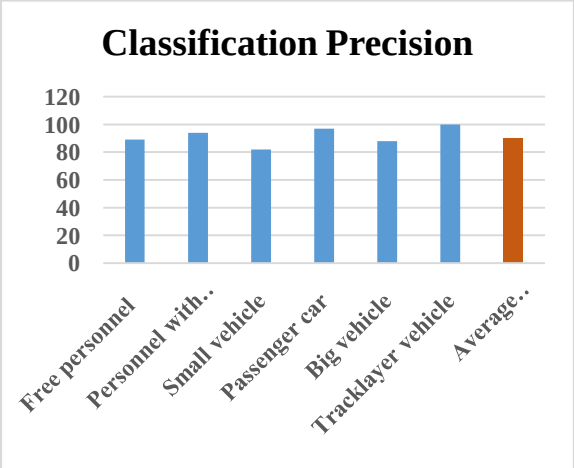

Figure 2: Statistical result of classification precision about six kinds of targets

4. Conclusion

Thus this project successfully detect the object using border surveillance system and also it classifies the object. A classification algorithm is based on the sensor network which adopts a peak and valley pattern of hybrid detection signals from different sensors.

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