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EMERGENT SITUATION AWARENESS OF DRIVABLE ROUTES FOR AUTONOMOUS ROBOTS USING TEMPORAL PROBABILISTIC REASONING

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ABSTRACT

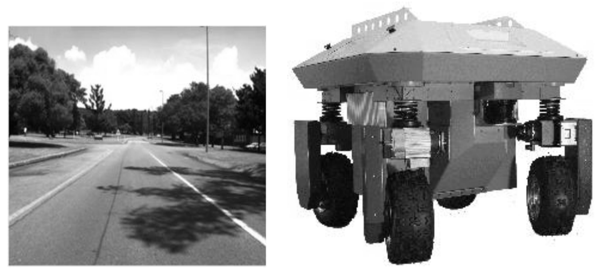
Researchers and practitioners have stressed that autonomous navigation in complex environments is an ongoing key challenge for robotic vehicles. Detection of drivable routes is often used as one of the important safety key operations to address some of the issues associated with autonomous navigation. While a number of conventional detection methods have been developed for such navigation; awareness of drivable routes by alleviating robot short-sightedness - without being trapped in uncertain dead-end problems, and to facilitating global navigational planning have received little attention. Finding a solution to these uncertainty problems is a challenge. In this paper, temporal probabilistic reasoning of the Emergent Situation Awareness (ESA) technology is proposed as a supportive strategy for autonomous navigation. The ability to reveal uncertainties over time is a drivable route awareness strategy of hidden paths embedded in the complex environments. Experimental evaluations of the ESA on real life and publicly available road frames outperform the classical statistical baseline methods in handling uncertainties over time. Our awareness results reveal to robotic vehicles that all ground planes are not traversable routes.

KEY WORDS

Robotics, Computer Vision, and Emergent Situation Awareness

1. Introduction

Safe autonomous navigation often formulates one of the significant objectives of robotic technology [1]. Researchers and practitioners have stressed that autonomous robotic navigation in complex environments as shown in Figure 1 is an ongoing key challenge [1] [2]. In practice, it is convenient to say that complex environments are relatively defined based on the percentages of mingled features such as colours of ground planes, bushes, and other objects perceived from left, centre and right sides of the environments. Since certain portions of ground are meant for say parking slots, one can see in Figure 1a that all ground planes are not traversable but most traversable routes are ground planes.



(a) An Outdoor Road Frame (b) Seekur Robotic Vehicle

Figure 1: A sampled outdoor road frame and a CSIR four-wheel platform synchronous drive robot, with three pairs of stereo vision cameras.

The complexity affects autonomous navigation and robotic research deliveries, and may hinder the growing usage of robotic vehicles in industries to save lives. For instance, robots are required to save lives from mining accidents, such as 4000 coal miners who died in China in 2006 [3] and 3000 people who were trapped underground in South Africa in 2007 [4]. From our practical knowledge, improving the performance of detection of drivable (or traversable) routes is obviously a sound basis for optimizing autonomous robotic navigation. Researchers [2] have presented related detection methods such as ensemble selection for road image classifications. This is an iterative scheme on a robot's motion that they still confirmed as prone to computational intensity and can slow down navigation. Our alternative approach is different from theirs as the environment model of interest herein is ready before the robot starts navigating. We therefore say that in order to travel fast and alleviate short-sightedness, the robot needs to be aware of traversable routes into a far distance. We shall first present the rudimentary details of our awareness strategy before its application in robotic vehicles.

Situation Awareness (SA) is to a notable extent becoming popular among decision makers. SA has gained its popularity in, for example, the areas of air traffic control, emergency responders, and surgical teams [6]. Instances of application areas where taking correct rapid-response decisions is needed are disaster management, business intelligence, robotics, even sport (e.g. robotic soccer) where players have to make instant decisions in a constantly changing environment. Most notably, there is an ongoing demand for SA technologies and their variants in environmental water management problems, in areas presenting human health risks and in robotic agents [6] [7]. Each of these problem areas is too complex to understand due to the uncertainties embedded therein, but compact representations of Bayesian Network (BN) models are effective in handling complexities.

Bayesian Networks (BNs) are probabilistic models that are gaining popularity in decision-making, such as robotic module deciding on which field classes are traversable routes. The major shortcomings of their current implementations include the inaccurate complex modelling despite expert intervention and the absence of complete temporal pattern modelling capabilities. The available DBNs (Dynamic Bayesian Networks) with temporal modelling, such as Factorial HMM (Hidden Markov Models), Coupled HMM, Input-Output HMM, and PDBN (partial Dynamic Bayesian Network) [8] [9] have contributed to modelling up to the baseline but they are explicitly represented by skilled users, therefore are limited in their expressive power. System Engineers such as robotic researchers and non-expert practitioners, struggle to interpret the DBN models to carry out a directed goal. This can make robots not being well acquainted with the situations of traversable routes currently occurring in their various domains. Finding a solution to this issue is a challenge, and the difference between poor and good autonomous navigation lies in their situational understanding of traversable routes over a distance.

In this paper, we achieve emergent situational awareness by evolving actual local dynamics from global emergent behaviours. The global behaviour is the temporal probabilistic model, which captures uncertainties of possible routes embedded in the environment. The local dynamics are the smallest pieces of information needed by robots for easily making correct traversable routes detection. For instance, when a robot is navigating, finding the best connecting drivable routes on a number of selected, rather than all routes within a space of time, is local dynamics. This paper aims to empower robotic autonomy using the ESA (Emergent Situation Awareness) technology to make the best possible detection from any recognized far distance situation at any time. The ESA technology; evolves DBNs from environments captured as MTS (Multivariate Time Series) in the absence of domain experts, views knowledge as situational patterns over time, and provides a suitable platform guide for robots on best detection processes. The major contributions in this paper are as follows:

- The integration and in-depth illustration of applying the ESA technology to optimize autonomous robot navigation through awareness of traversable routes over a long distance.
- The evaluation of the ESA on publicly available road frames compared with classical statistical methods, which researchers often use as a baseline of comparisons to new approaches.

The rest of this paper is arranged as follows: in section 2, we present the theoretical background of the ESA as a class of DBN or temporal probabilistic models. Section 3 presents the proposed technology, which includes the system model and algorithm of the ESA. Section 4 rigorously presents experimental applications and evaluations of the ESA on autonomous robotic navigation through the awareness of drivable routes. We conclude the paper in section 5.

2. Theoretical Background of the ESA

2.1 Dynamic Bayesian Networks (DBNs)

The simplest form of DBN is shown in Figure 2.

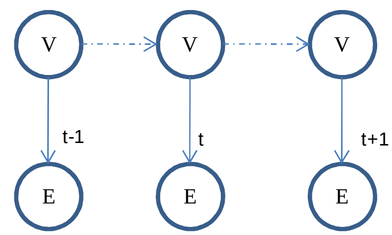


Figure 2: The simplest DBN is Hidden Markov Model with V as state variables and E as evidence variables repeated in three time steps.

DBNs are temporal probabilistic models which are often referred to as an extension of the Bayesian network (BN) models in artificial intelligence [8]. A Bayesian belief network is formally defined as a directed acyclic graph (DAG) represented as G = {V(G), A(G)}, where V(G) = $\{V_1,\ldots,V_n\}$, vertices (or variables) of the graph G and $A(G) \subseteq V(G) \times V(G)$, is the set of arcs of G. The network requires discrete random values such that if there exists random variables $V_1, \ldots, V_n$ with each having a set of some values $v_1, \ldots, v_n$ then, their joint probability density distribution is defined in equation (1);

$$pr(V_1,...,V_n) = \prod_{i=0}^{n} pr(V_i \mid \pi(V_i)) \qquad (1)$$

where $\pi(V_i)$ represents a set of probabilistic parent(s) of child V_i [10]. A parent variable otherwise referred to as *cause* has a dependency with a child variable known as *effect*. This is similar to variables V and E in a time step of Figure 2. Every variable V with a combination of parent(s) values on the graph G captures probabilistic knowledge (distribution) as a conditional probability table

(CPT). A variable without a parent encodes a marginal probability. If the environment is small, a BN can be modelled by eliciting the probabilistic knowledge from domain experts. For more complex domains such as traversable routes, the most suitable Bayesian networks are learned from the environments captured as datasets. Intelligent system researchers such as [11] [12] have presented many algorithms to learn Bayesian networks from datasets. Its characteristics of capturing dependencies variables make it suitable for handling complex problems [7].

However, the inability of the BNs to capture time as temporal dependencies facilitated the development of various ways of modelling the dynamic Bayesian networks presented in the introduction. The variables and the CPTs of the BNs are similar to the states and the probabilities used in the temporal dependencies of the DBNs. According to [7], a DBN is suitable for modelling environment that emerges (changes) over time and has the capability to predict future behaviour of the environment. In this research, we want to predict the most likely paths that robots must traverse that are not known based on the current situations robots understand. Most DBNs observe the first-order of the Markov model which states that a future event V_{t+1} is independent of the past given the present V_t [7]. The probability is represented as $Pr(V_{t+1} \mid V_t)$. The states of events in a DBN have complex interaction due to the time dependency and may impact on the observed variables of the DBN at any time step.

Let V_i^t represent DBN variables of the ESA at time t; we derive the following equation (2) from equation (1), over all the non-negative time steps $t \in T$, where T = {total time steps over the target areas} e.g. road frames, and t = {the time step within the volume of an area} e.g. an image frame.

$$pr(V_1^t, V_2^t ..., V_n^t) = \prod_{i=0}^{n} pr(V_i^t \mid \pi(V_i^t)), \ \forall \ t \in T \qquad (2)$$

The system of equation (2) forms temporal dependency relations between the time slices as shown in equation (3), which generates a matrix of transition knowledge embedded in the environments captured as MTS.

$$pr(V_1^1, V_2^1 ..., V_n^1) \overset{\Delta}{\equiv} pr(V_1^2, V_2^2 ..., V_n^2) \overset{\Delta}{\equiv} pr(V_1^t, V_2^t ..., V_n^t) \qquad (3)$$

$\overset{\Delta}{\equiv}$ implies that equivalence is *not* true generally.

From equation (3), the relationships embedded among variables V at time step 1 may or may not be equivalent to the variables' relationships at time step 2, and for subsequent time steps t. This is as a result of the changes in environmental patterns, which affect the relationships of the model variables over time. Such model is exemplified as vertices and arcs shown as part of Figure 4. Unlike most DBNs in literature, equation (3) is a DBN that varies both its probabilistic distributions and its temporal DAGs by learning directly from MTS, which captures environmental features such as the road features. The relationships here are of greater value to situation awareness because hidden situations are revealed over time.

2.2 Situation Awareness

Situation Awareness (SA) refers to, "…the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future [5]." The most established SA theory is described in a popular model in Figure 3 which describes the current situation model as a mental model at three hierarchical levels. As shown in Figure 3, level 1, 2, and 3 of SA correspond to *perception*, *comprehension* and *projection* respectively. The three components are the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future.

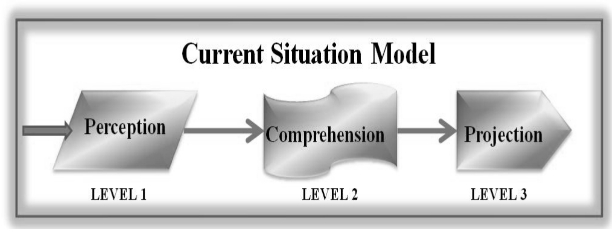


Figure 3: A Hierarchy of Mental Model [5].

SA therefore enables a robot to recognize what situation is going on in its domain of interest in order to figure out what to do next. Thus, the temporality link between the theory of SA and the theory of DBNs motivated the development of the ESA and its applications in [13].

3. The Proposed Technology for Robotics

3.1 The System Model for the ESA

The system model in Figure 4 comprises three essential components, which are learning algorithms, probabilistic distributions and the trend analysis. The first two components collectively achieve Figure 3 by discovering the system knowledge, which is integrated into the third component called the interface knowledge. The robot uses this knowledge as a platform to understand traversable routes ahead.

In Figure 4, the Learning Algorithms dynamically evolve temporal models from the collection of pixels embedded in the multivariate time series (MTS). The MTS is observed over the collection of pixels extracted from frames and serves as input for the learning model. The algorithms emerge interlink temporal models from *frames 0* to *n*. The existing learning algorithms such as genetic algorithms (GA) [11] [12], which are used for learning BNs from datasets, fit into Figure 4, if upgraded to learn over time. The optimized GA in [12] is upgraded to evolve over time and is used as a proof of concept in this system model. The algorithm uses information-theoretic measures (e.g. Minimum Description Length) and mathematical components (e.g. PowerSet in set theory) as genetic operators and as a means of balancing between efficiency and decomposability. The GA is used due to its efficiency as it performed very well when used to emerge models from the environments of numerical, nominal and mixed datasets.

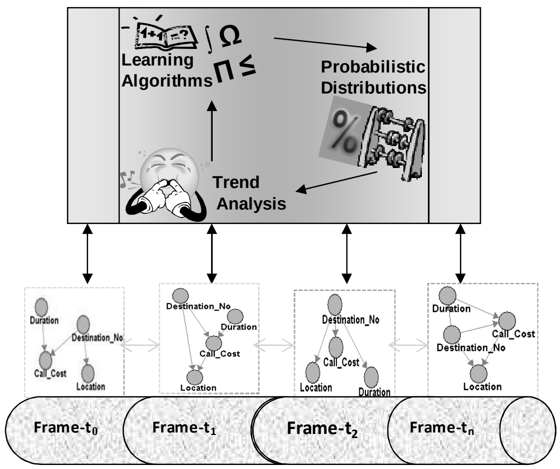


Figure 4: A System Model for the ESA.

The other functionality of the probabilistic distribution integrated into Figure 4 is a Bayesian inference of the Variable elimination algorithm [7], which is used to reason and detect traversable routes over time. This reasoning algorithm is based on Bayes' theorem [10], expressed as posterior probability in equation (4) for some random variables V_s and V_e. The V_s implies state variable of the model while V_e implies evidence variable.

$$\Pr(V_S \mid V_e) = \frac{\Pr(V_e \mid V_S) * \Pr(V_S)}{\Pr(V_e)} \tag{4}$$

The component of trend analysis in Figure 4 is an interface that constructs a transition matrix of knowledge on traversable routes over time using the inference algorithm. The nature of knowledge in the patterns generated can determine the likely navigational action to be taken on any traversable situation n to arrive at (or avoid) the next situation $n+1$. In applying this technology, especially by robotic researchers or non-expert practitioners, we formally present the ESA algorithm as shown in Figure 5.

3.2 The ESA Algorithm

An MTS serves as the required schema to Figure 5, but the additional capability of the ESA algorithm in Figure 5 serves to generate MTS from domain datasets without changing their originalities. Its development is based on the theories, algorithms, models and mathematical analysis, which are used as subroutines as presented in the previous sections.

In Figure 5, the D_{sj} is a column of the schema, d_t is a frame dataset and b_t is a temporal Bayesian Network emerged at time t. As shown in step 1[*i*], discretization classifies numerical datasets into their corresponding interval values relative to the patterns in the data attributes. Due to the predominance of computational intensity during data-preprocessing, the ESA introduces scalability into the discretization processes. In this scheme, space is shared and every used memory is cleared for the next processes. In step 1[*v*], the Bayesian learners are any of the algorithms that were recently mentioned [11] [12], whose functionalities are to carry out intra-slice learning over time. They emerge temporal optimal BN at each time step. Likewise, the Bayesian inference generates several situational trends as a transition matrix of knowledge, which is consequently used to reveal drivable routes.

Revealing hidden traversable routes is made simpler with the ESA, as robots can now be well acquainted with their current complex domains before projecting over a long distance. Since the ESA is domain-independent, it not only accommodates highly skilled users, but also allows non-expert robotic practitioners to benefit from temporal probabilistic modelling.

INPUT (D_s : Dataset Schema)

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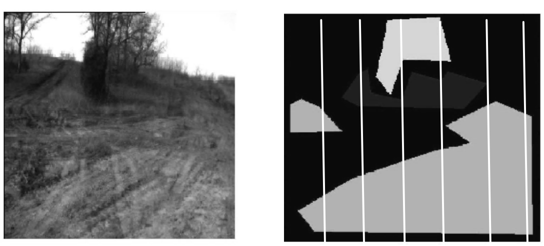
1. While D_s = MTS,
   - [i] If D_{sj} = *Numeric*, for $j = 0, 1, 2. . . m$.
     - Call Scalable_Discretizer (D_{sj}).
   - [ii] Perform ordering on D_s using t key.
   - [iii] Set t, the frame count, to 0.
   - [iv] Let $d_t \in D_s$, $\forall$ $t = 0, 1, 2, . . ., n$.
   - [v] For each $t <= n$,
     - Select frame d_t for emergence.
     - Call Bayesian_Learner (d_t).
     - Store the emerged temporal BN in matrix B.
     - Increment t by 1.
   - [vi] For Situational Trends, Call Probabilistic Distributions, $\forall$ $b_t \in B$.
   - [vii] Return the dynamic BNs in B as the frames' situations, then exit.
2. While D_s <> MTS,
   - [viii] If D_{sj} = *Date*,
     - Select t.
     - Generate MTS from D_s using t.
   - [ix] Repeat step 1.

Figure 5: Emergent Situation Awareness (ESA) Algorithm.

4. Experimental Evaluations on Traversable Routes for Robotic Vehicles

One of the objectives of this paper is to bring the theory of the ESA technology to practice with an emphasis on robotic applications and practical work on the awareness of traversable routes. It consequently alleviates the robot's short-sightedness and avoids being trapped in dead-end paths. This is an optimization strategy for autonomous robotic navigation. To justify the universality of the ESA and to assure that our modelling design is reproducible, real life and publicly available road images are used to test our theories and implementations. Three experiments were conducted on some complex environments including (1) public road images collected by a robotic vehicle [14] and (2) CSIR real life road frames captured locally.

The public road images, whose example is shown in Figure 6, were provided with labelled colours, where the light-blue portion depicts a ground plane, the red (or dark) class depicts grass, the yellow (or lightest) class depicts tall vegetation and the deep-blue (or very dark) corresponds to an unlabelled (or uncertain) portion. The objective relevant to our work herein is for robots to autonomously understand the situations in a long range and find the best paths to traverse from one frame to the other, especially on the uncertain areas. Seven of the images, which contain traces of several ground colours were connected as a set of contiguous frames F_i, such that traversal starts from $\{F_{18}\text{-}F_{16}\text{-}F_{14}\text{-}F_{13}\text{-}F_{10}\text{-}F_7\text{-}F_4\}$ [14] and are depicted as $\{F_1, F_2, ..., F_7\}$ respectively.



(a) Original Public Road (b) Labelled Road Frame

Figure 6: An original public road and its labelled frames from Bayesian fusion repository [14].

A MTS (multivariate time series) dataset was captured from this environment where each frame is partitioned into seven column grids of $\{X_1, X_2, ..., X_7\}$, representing possible robot traversable pathways and consists of an average of 45 row grids. The colour features and their areas or sizes are estimated from each window grid and the resulting MTS is used by the ESA software to emerge the appropriate temporal probabilistic model.

Similar streams of frames were perceived from CSIR campus roads, such as a frame result shown in Figure 7, where each frame is partitioned into three columns of left, centre and right grids. The frame partition also includes three row grids with the horizon being ignored. These frames are run through an image processing tool in MATLAB, where low level analysis per pixel with a 9 by 9 support window is carried out. This analysis operates on a defined colour band in the RGB colour space, and the instances of traversable paths are labelled as states {LD, CD, RD, dead-end}. The states imply left, centre, and right drivable respectively, where dead-end is not a drivable portion. This means that each of the four states has 25% equal chances of being the most probable result of drivable routes. With a similar objective as the public roads above, the areas of these colour features are similarly estimated and the resulting MTS in a tabular structure is used by the ESA software to emerge temporal probabilistic model.

4.1 Experiment 1: Illustrating the Awareness of Best Traversable Routes for Robots

Having captured the models of the road environments, the robot acts on these models either before or during autonomous navigation to understand situations ahead. An effective stereo camera mounted on the Seekur robot perceives new environmental frame features from a long range, which are used to query or reason on the model in less than a second to detect and enable the robot to understand the drivable paths on CSIR roads. A probabilistic query example is illustrated in equation (5) and its detection results are shown in Figure 7. Equation (5) acts on the temporal model emerged and overlay predicted drivable results on its image frame in Figure 7. As new frames arrive, their corresponding temporal models are acted upon accordingly. More information on inference is provided in [7].

$$pr\,(\textbf{Drivable}^{t}\,?\,|\,\mathrm{LC}^{t} = 0.62,\ \mathrm{LSize}^{t} = 9\%,\ \mathrm{CC}^{t} = 0.6,\ \mathrm{CSize}^{t} = 10\%,\ \mathrm{RC}^{t} = 0.62,\ \mathrm{RSize}^{t} = 13\%) \quad (5)$$

Equation (5) is a Bayesian inference problem which uses equation (4) and becomes:

$$\frac{\Pr(LC^{t} = 0.62, ..., RSize^{t} = 13\% \mid Drivable^{t}) \times \Pr(Drivable^{t})}{\Pr(LC^{t} = 0.62, ..., RSize^{t} = 13\%)}$$

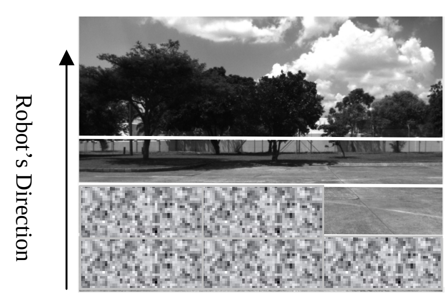


Figure 7: Awareness results of drivable routes on CSIR road over a long range with a 77% probability of having dead-end, 40% for next LD and CD results, and 39% for having last results, far above the 25% equal probability as degrees of beliefs.

On the query of features situation in equation (5), the robot wants to know the *most* probable and drivable areas of Figure 7 for example, when the road features situation (e.g. LC = left colour with grey saturation 0.62, its left colour size (LSize), etc.) are perceived over a distance. From our temporal probabilistic modelling framework, it should be noted that the features, which are the evidences perceived along robot's direction, change within the space of time in the queries such as equation (5). One can see in Figure 7 that the ESA reveals a dead-end ahead of robot's direction and confirms that all ground planes are not drivable.

Understanding best traversable routes on the public roads before the robot starts navigating becomes essential to meet up with the ever changing complex environment (e.g. Figure 6). Robots may issue any probabilistic queries similar to equations (6) and (7) which act upon the model and create awareness results about traversable routes as shown in Figures 8 and 9. In equations (6) and (7), the robot wants to understand the most probable and traversable routes on Figure 6 for example, given the features perceived over all the seven frames tested.

$$pr\,(\mathbf{Routes}^{t}\,?\,|\,X_7\_\mathrm{Colour}^{t} = \textit{deep-blue},\ X_7\_\mathrm{Area}^{t} = 60{<=}90\,\%) \qquad (6)$$

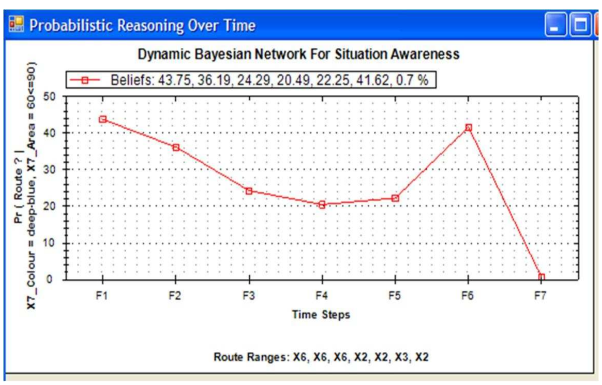


Figure 8: Emergent Situation Awareness of traversable routes on public roads given that route X_7 often contains at least 60 to 90% of deep-blue (uncertain) colour features.

As shown in Figure 8, the ESA reveals the best traversable routes of X_6 to X_2 on frames F_1 to F_7 respectively with their corresponding strong degrees of beliefs (or probabilities) higher than 14% equal chances of selecting each route. Figure 9 reveals the patterns and summarises the competitions of routes $\{X_1,...,X_7\}$ to be selected as most probable and traversable over the 7 frames. On Figure 9, the results show to the robot that the best traversable route on road frames F_1 to F_4 is X_2 with varying probabilities.

$$pr\,(\mathbf{Routes}^{t} = X_i\,?\,|\,X_1\_\mathrm{Colour}^{t} = \textit{deep-blue},\ X_1\_\mathrm{Area}^{t} = {<=}15\%) \qquad (7)$$

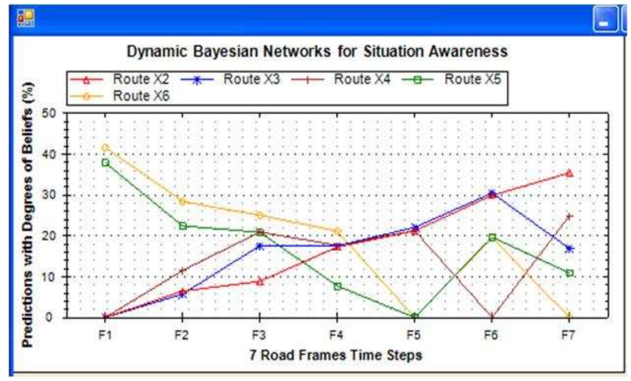


Figure 9: Summarised competitive traversable routes on public roads given that route X_1 often contains at least 15% of deep-blue colour features.

4.2 Experiment 2: Empirical Evaluations on the Awareness of CSIR Drivable Routes

The objective here is to find the impact and performance of the ESA on the awareness of traversable routes. A scientific method used is a 90% training and 10% test frames situations of the multiple cross validation technique [7]. It is an unbiased method where the perceived test feature situations are selected at random from known road frames as expected results and traversable routes are predicted by the ESA model emerged from the remaining training sets. The results depicted by Table 1 are a summary of the average performance accuracy of the ESA on the CSIR roads in terms of expected and predicted drivable results.

Table 1: Performance Accuracy of the ESA Technology on Awareness of Drivable Routes.

Road Datasets	**Features Situations**	**Expected Drivable**	**Predicted Drivable**
	$\Pr(\mathrm{Drivable}^{t}\,|\,s_1),\ t = F_{230}$	LD,CD,RD	LD, RD
	$\Pr(\mathrm{Drivable}^{t}\,|\,s_2),\ t = F_{215}$	Dead-end	Dead-end
CSIR	$\Pr(\mathrm{Drivable}^{t}\,|\,s_3),\ t = F_{305}$	CD, RD	CD, RD
	$\Pr(\mathrm{Drivable}^{t}\,|\,s_4),\ t = F_{185}$	Dead-end	Dead-end
	$\Pr(\mathrm{Drivable}^{t}\,|\,s_5),\ t = F_{305}$	CD	CD
Accuracy	**92%**		

The test features' situations are depicted as s_i, where for example s_1 = {LC ^{t} = *0.65*, LSize ^{t} = *97%*, CC ^{t} = *0.65*, CSize ^{t} = *100%*, RC ^{t} = *0.65*, RSize ^{t} = *100%*}, from frame 230 and s_5 = { LC ^{t} = *0.58*, LSize ^{t} = *5%*, CC ^{t} = *0.6*, CSize ^{t} = *90%*, RC ^{t} = *0.62*, RSize ^{t} = *10%*} from frame 305. The perceived situations, s_i, are used similarly like the probabilistic query in equation (5), which thereafter uses equation (4). The ESA detected only 2 drivable paths instead of 3 on the first result of Table 1. However, by comparing the expected and the predicted drivable results, observe the overall accuracy of 92%. This suggests that integrating the ESA on robots for traversable route awareness is a solution to alleviate short-sightedness and supports accurate autonomous navigation.

4.3 Experiment 3: Comparing the ESA with Classical Statistical Methods on Public Roads

Bayesian network modelling technologies have been compared with other AI (artificial intelligence) techniques such as neural networks and ruled-based techniques in recent scientific research. The probabilistic networks showed better performance over these techniques in water analysis [6]. This experiment therefore evaluates the ESA with classical statistical methods, which researchers often used as a baseline of comparisons in handling uncertainties. The classical statistical methods use the frequency concept of probability [7] to handle uncertainties, while the temporal probabilistic modelling of the ESA uses Bayes' theorem [10] over time.

Table 2: Comparing Classical Statistical Methods and the ESA in Handling Uncertainties.

Probabilistic Features Situations (unobserved)	**Frequency Concept of Probability**	**Temporal Probabilistic Reasoning – ESA**
Pr(**Routes**^{t} | s_6), t = Frame-1	0.0%, unknown	5.45%, X_6
Pr(**Routes**^{t} | s_7), t = Frame-2	0.0%, unknown	8.85%, X_6
Pr(**Routes**^{t} | s_8), t = Frame-4	0.0%, unknown	3.50%, X_2
Pr(**Routes**^{t} | s_9), t = Frame-5	0.0%, unknown	5.20%, X_2
Pr(**Routes**^{t} | s_{10}), t = Frame-6	0.0%, unknown	5.71%, X_3

The uncertainties imply that if a set of unobserved road situations is perceived during navigation, how will the robots handle it? That is supposing the environment slightly changes or certain features are omitted during modelling and the stereo camera observes unforeseen feature situations $\{s_6, ..., s_{10}\}$ afterwards from some frames 1 to 6 respectively as summarised in Table 2. For instance, suppose the robot's sensor perceives situation s_6 = {X_4_Colour ^{t} = *red*, X_4_Area ^{t} *>90%*, X_7_Colour ^{t} = *red*, X_7_Area ^{t} = *10<=40%*} from the middle of Figure 6b, where grass (or red) is not present on route X_7. Computing statistical frequency concept of probability on s_6 from its frame learning sample resulted in 0% probability, which implies unknown routes. This is an uncertainty problem, which is not informative enough for robot to know which path to traverse from one frame to another. We therefore used the emerged ESA model for reasoning with a sampled set of probabilistic situations shown in Table 2 using both approaches, but found that the results of the temporal probabilistic model of the ESA outperforms the classical methods in handling such uncertainty.

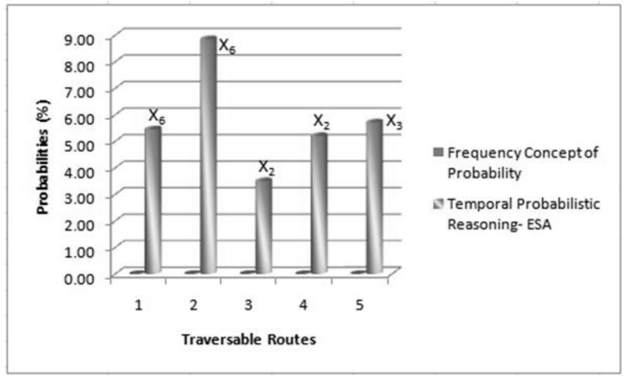


Figure 10: Visualising Capability of Handling Unforeseen (Uncertainty) Situations on Public Roads.

Observe zero degrees of beliefs (or probabilities) of unknown routes for all situations chosen at random on the statistical methods column in Table 2. However, the ESA is still able to predict traversable routes for robots with minimal beliefs. We understand that this is because the classical statistical methods assume that all possible ground situations must be observed at modelling [7], but this is not true in the real life of uncertainty, especially in robotics. These results are visualised as shown in Figure 10 as one can recall that the ESA uses Bayes' theorem to handle the uncertainties over time.

5. Conclusion and Future Work

In this paper, we have described the theories and illustrated the application of the temporal probabilistic reasoning technology, ESA, to awareness of drivable routes in robotics. This contributes to effective autonomous navigation and alleviates short-sightedness since robots can now understand situations in a far distance with its mounted stereo camera perceiving long range road features.

This study shows that the ESA will potentially one day become a powerful technology used by researchers and robotic vehicles to understand long range field situations as it contributes to optimization of autonomous navigation. This technology simply emerges from complex environments and predicts traversable routes for robots. Our results confirm that all ground planes are not drivable. Its empirical evaluations measure its reliability as 92% in awareness of CSIR drivable paths as summarised in Table 1. The results of the five probabilistic situations on public roads in Table 2 and Figure 10 also show that the temporal probabilistic reasoning of the ESA outperforms the classical statistical methods in handling uncertainties embedded in robotic road environments. Interestingly, integrating this work into other robotic modules (e.g. path planning, etc.) would result in diverse real life problems (e.g. various mining accidents) being solved with autonomous robots. We are currently working on integrating scalability into the ESA to handle possible massive MTS or computations for robots.

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