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Application of a Counter Propagation Neural Network for Star Identification

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During research underway at the Queensland University of Technology in the area of satellite technologies, the need for a fast, accurate and reliable star identification method presented itself. This paper presents one approach to solving this problem in a non-conventional manner. A Counter Propagation Neural Network has been implemented and tested producing favourable results. Presented in this paper is the incorporation of the Counter Propagation Neural Network into the star sensor, the network structure, simulations of implementations and results.

I. Introduction

THE identification of stars for attitude determination has posed many problems over the years. Each implementation has to make the best use of the available features of the star sensor system. The desired accuracy, functionality and reliability need to be considered when choosing a star identification method. Traditional approaches focus on the use of extracting star triangle data and comparing this to a stored database of possible star triangles. This approach presents two major problems: the star selection method used to build the star triangle, and the organisation of the star database.

There are a few approaches to tackling the problem of star selection and they are covered in depth by such researchers as Liebe[1], Quine[2,3], and Douma[4]. A variation of these approaches is presented that uses more stars than the traditional approaches that use sets of three.

The second major problem is the organisation of the star database and this problem has been researched in depth in recent years[1-4]. The star database must be able to cope with the inaccuracies present in the original star catalogue, which was used to generate the database, and also from the sensor measurement errors. This has resulted in the trend of quantising the database entries to an acceptable limit and in some cases having entries for all possible combinations of measurement plus error included. As a result there can be multiple entries in the database for each star triangle.

This paper presents an alternative to this approach where the star identification information is stored in a neural network with no duplication. The neural network is inherently able to accommodate the error in the sensor measurement and the star catalogue. The advantages of using Neural Networks to solve this problem were highlighted by Bardwell[5], and the success of this work has been the motivation for this research.

A Counter Propagation Network (CPN) has been chosen for this research. This is a classification network that, in its simplest form, takes a feature vector input and gives an output of what it has classified it as and the probability of the classification being correct. The classification in this case is the identity of an input feature vector and hence the absolute position of the stars used to make up the vector.

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II. Star Feature Selection

The star feature selection must be developed so that its performance is repeatable on the star sensor hardware. The focus of this implementation for the star identification algorithm is based upon available existing hardware, with the specifications listed in Table 1.

Table 1 Star Camera Specifications

Manufacturer	Kayser-Threde
Camera	KM 1301
Field of View	21^0 x 31^0
CCD	288 x 384

Table 1 shows that the star sensor field-of-view is 21^0 x 31^0. The use of a different star sensor, with different field-of-view specifications, could affect the star selection process described below. As this investigation is primarily concerned with the star identification utilizing existing hardware, no detailed analysis will be conducted of the effects of different fields of view. The general trend of a narrower field of view camera being able to detect fainter stars, leads to the assumption that providing the star coverage is sufficient, the system should work. It should also be noted that a camera with a field of view of 20^0 x 20^0 would operate in an identical fashion to what is described in this paper.

The Counter Propagation Network (CPN) accepts a feature vector as input. This must be consistent to allow for reliable results. This translates to ensuring that a training vector for the CPN is made which can be replicated by the star sensor. An important aspect of the feature vector is that it has to be made from rotationally independent parameters and therefore only relative measurements can be utilised. Rotationally independent parameters are values that can be consistently measured regardless of the orientation of the image.

The training vectors are created by the following process:

1. Mark all stars with a magnitude above a predetermined level as ‘Guide Stars’
2. For each guide star collect the brightest stars outside a radius of 0.5 degrees and within a radius of 5 degrees and mark as ‘Secondary Stars’
3. Translate the great circle angular distance from the ‘Guide Star’ to the ‘Secondary Stars’ into the target star sensor units of measurement, $R_{gs-1}, \ldots, R_{gs-x}$
4. Calculate the angular separation from the ‘Guide Star’ and the brightest ‘Secondary Star’ to all other ‘Secondary Stars’, $\theta_{1gs2}, \ldots, \theta_{1gsx}$
5. Build the vector as $R_{gs-1}, \ldots, R_{gs-x}, \theta_{1gs2}, \ldots, \theta_{1gsx}$

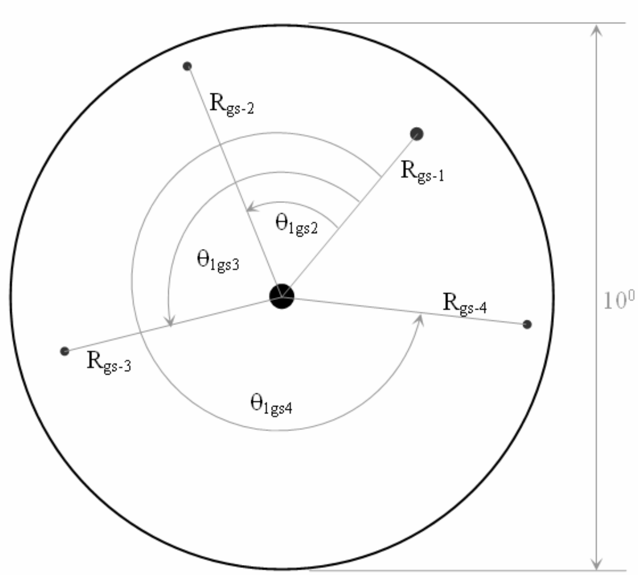

Figure 1 Feature Vector Generation

It is important to note that the selection of the magnitude for guide star must be undertaken carefully to ensure that there is a full coverage of the sky. A program has been developed to give a visual representation of the sky coverage at a given magnitude limit. This allows the selection of the magnitude level for the cut off of guide star selection trivial. Figure 2 illustrates the guide star magnitude level cut off and the sky coverage used in the simulations within this paper. Areas of green are within 5^0 radius of a guide star, areas in light yellow are within 10^0 of a guide star, and red areas are outside the 10^0 radius from all guide stars.

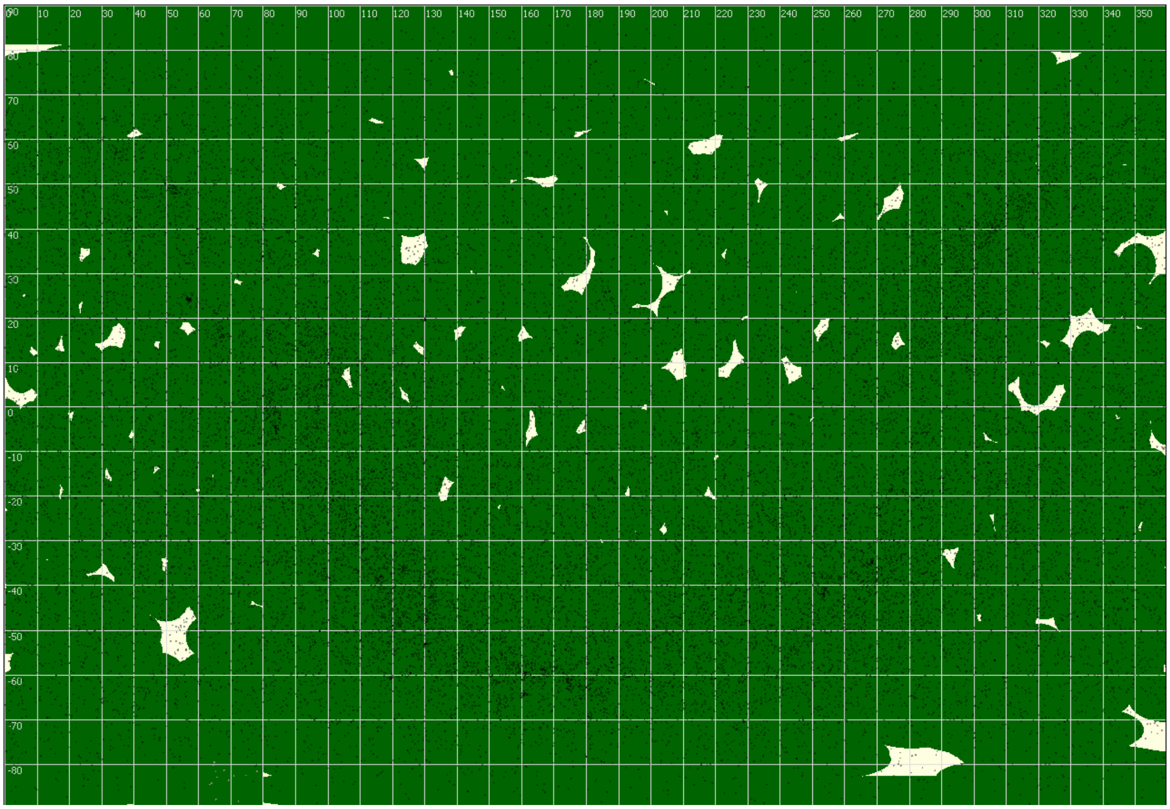

Figure 2 Star Magnitude Sky Coverage

The star catalogue that the feature vector is to be built from requires several steps of pre-processing to be carried out before it can be used. The process for this is listed below.

1. Magnitude conversion from visual magnitude to the corresponding magnitude for the target star sensor
2. Propagation of the star positions to the relevant date
3. Merging of stars that have a small great circle angular distance to overcome the apparent merging that takes place during the blurring in the centroiding process

The above process results in vector representations of a number of star sets, which can then be used to train the CPN. Determining an appropriate length for the input feature vector for this application is explored in detail within section V.

The process of recreating a star feature vector from the star sensor image is described below:

1. All stars within the 'Valid Guide Star Region' are marked as possible guide stars
2. A feature vector is constructed for the brightest possible guide star and its surrounding secondary stars
3. This feature vector is run through the CPN and if the probability value of the solution is acceptable then the solution is accepted, otherwise step 2 is repeated for the next most likely feature candidate until an acceptable probability value is obtained.

Figure 3 illustrates the star sensor field-of-view and possible stars for a feature vector. It can be seen that the exclusion zone of 5^0, for the guide stars, around the edge of the field of view, eliminates the chance of choosing a guide star for which the full feature vector stars are not viewable.

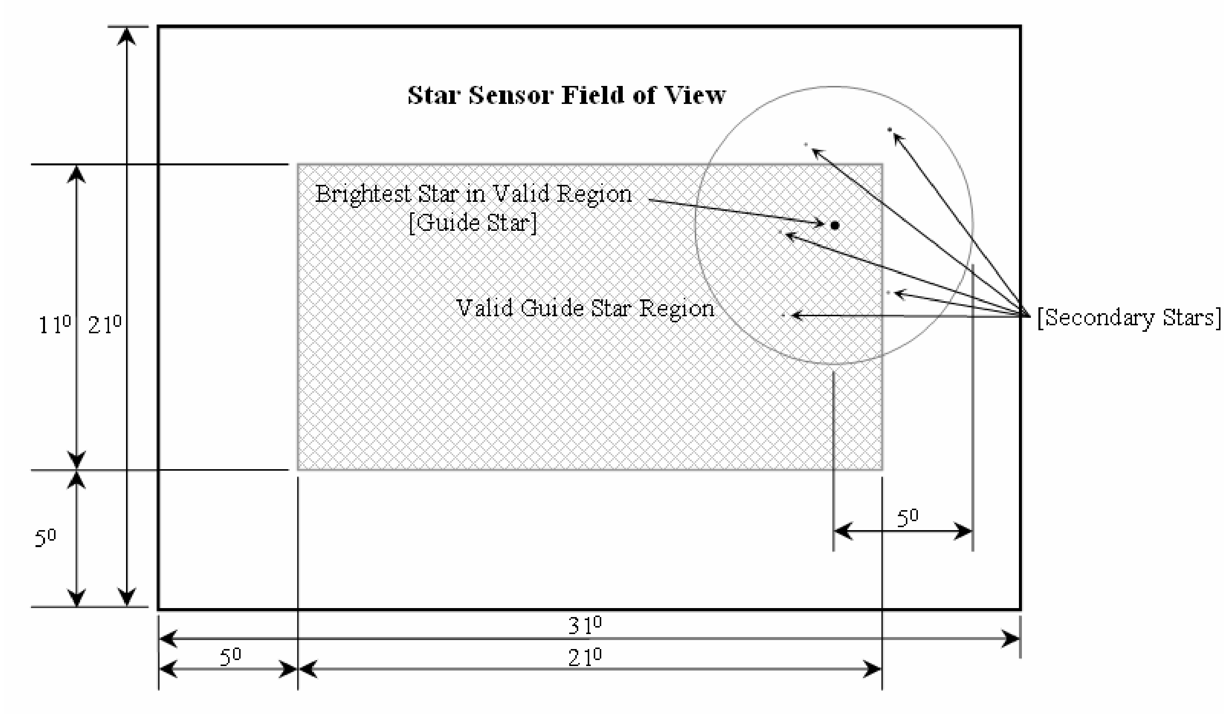

Figure 3 Star Sensor Star Selection

The radius of the star selection, 5^0 in this case, is crucial. It must be large enough to include sufficient stars for reliable identification but small enough to not exclude too much of the field-of-view of the star sensor. A case may exist where there are insufficient stars, of an appropriate magnitude, to construct the feature vector. This is not a critical problem as the remaining feature vector elements can be zeroed with little effect in performance.

If a camera with a different field of view was used then the star selection radius parameter would have to be adjusted and examined for its possible impact.

III. Neural Network Structure

The neural network implemented for this research is a Counter Propagation Network which was developed by Robert Hecht-Nielsen[6] as a means to combine a traditional unsupervised Kohonen layer and a teachable output layer. The CPN is designed to solve the complex classification problem whilst minimising the number of processing elements and the training time. It can be viewed as a self-programming lookup table as it essentially finds the closest fit of a particular input to an entry in its training set. A crucial feature for this application is the ability to accept input with noise and provide a solution and probability value for that solution.

A special feature of the Counter Propagation Network exists if the function can be linearised. This CPN network adaptation is referred to as Interpolative Associative Memory and has the substantial benefit that it does not require training in the traditional sense. It is this CPN adaptation that has been implemented in this research.

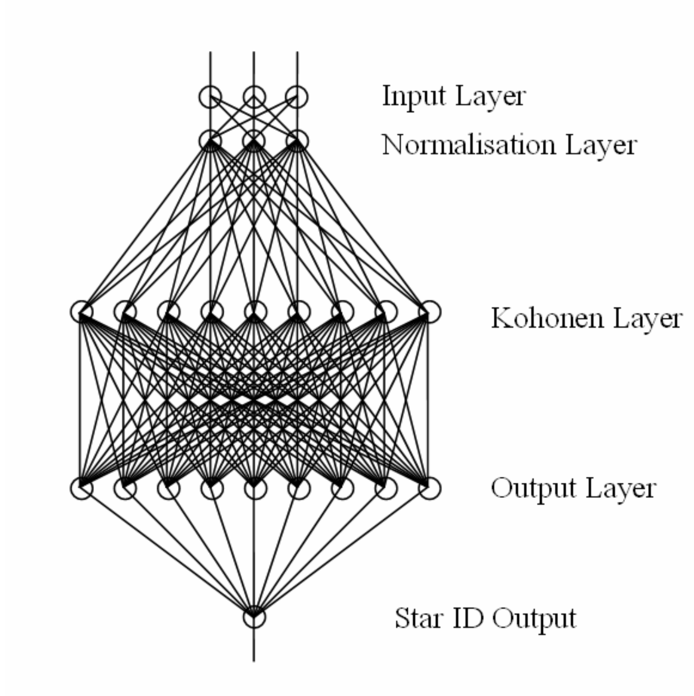

Figure 4 CPN Implementation

For the CPN to operate, the input feature vector must be constructed and normalised. The construction of the input feature vector was described in previous sections. The input layer can be expanded or contracted depending on the number of features to match against. The normalisation of this vector is performed by the first layer of the neural network. The length (number of input neurons) of the input feature vector is dictated by the number of star pattern characteristics that are to be used.

The Kohonen and output layers contain as many neurons as there are training feature vectors. The Kohonen layer learns to associate an input vector with one output neuron as it is a winner takes all system. Only one output layer neuron will win and that corresponds to the particular class it that is best fits. The magnitude of the winning neuron in the output layer also gives a probability value as to how well it fits the class. The star ID output layer simply takes the winning output neuron and relates this to the positions for all stars that are used to construct the input feature vector.

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IV. Star Sensor Integration

The integration of this type of star identification method into a star sensor is hardware dependant. There are mainly two dependant factors of a star sensor that have to be considered when choosing this method:

1. Field-of-view – the field-of-view of the target camera has a bearing on how the input feature vector is constructed.
2. Onboard processing power - the onboard processing power has a bearing on the number of training feature vectors that the network is able to remember and compare the input against in a single epoch. The length of the input feature vector also has a direct correlation to the processing power that is used for a single star identification. Presented in this paper is a star identification method, not an attitude determination method, therefore there has to be consideration given to the processing for the attitude calculation once the stars have been identified.

V. Simulation Results

All tests were conducted using an array of input feature vector lengths from 3 to 17. Training feature vectors are generated and introduced into the system. The system is then tested with test input feature vectors built from the training feature vectors stars with the addition of varying amounts of capped random star position error, in Right Ascension (RA) and Declination (Dec), of 0.0005 (1.8 arc seconds) to 0.025 degrees (1.5 arc minutes). The star position error introduced by the quantisation in the CCD array (288x384 pixels) of the star sensor is in the order of 0.0045 (16.2 arc seconds) degrees.

There are a few key features that have been focused on in the testing and they are:

1. Success rate of correct star identifications
2. Highest probability value for a failed star identification
3. Lowest probability value for a successful star identification
4. The percentage of successful star identifications that can be guaranteed based on probability value
5. Processing time of star identifications

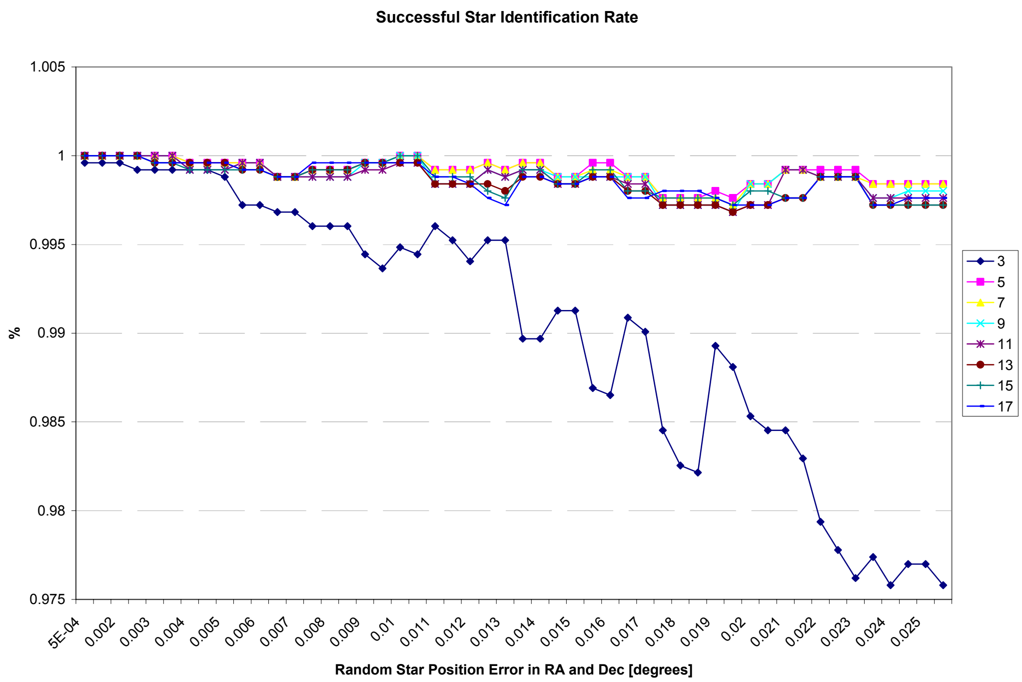

Figure 5 Successful Star Identification Rate

The success rate is a crucial aspect of this system as incorrect star identifications, whether identifiably incorrect or not, affects the overall performance of the system. Input feature vectors of length 3 to 17 have been tested and are illustrated in Fig. 5. The overall trend, with the exception of feature vector length 3, is for the smaller element input feature vectors to have a slightly higher success rate. The success rate for all input feature vectors except length 3 vary from 100% to 99.54%. The input vector of length 3 successful star identification rate degrades rapidly with the increase of induced error compared to all other input feature lengths.

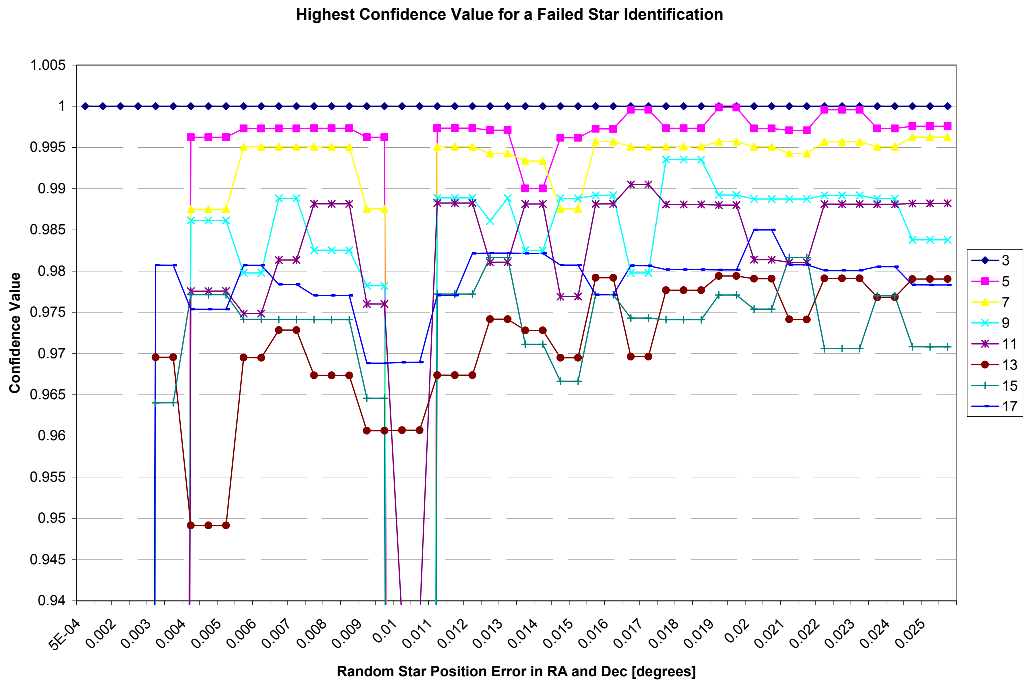

Figure 6 Highest Probability Value for a Failed Star Identification

The probability value is an indication of how well the input feature vector matches the output classification based on the training vector. It is advantageous for a failing star identification to have a low probability value so it is easily recognised as a failure. Figure 6 shows that the larger the input feature vector length, the lower the probability value is for failed (incorrect) star identification. This is expected as the larger amount of features to match against should logically give a clearer indication of success or failure.

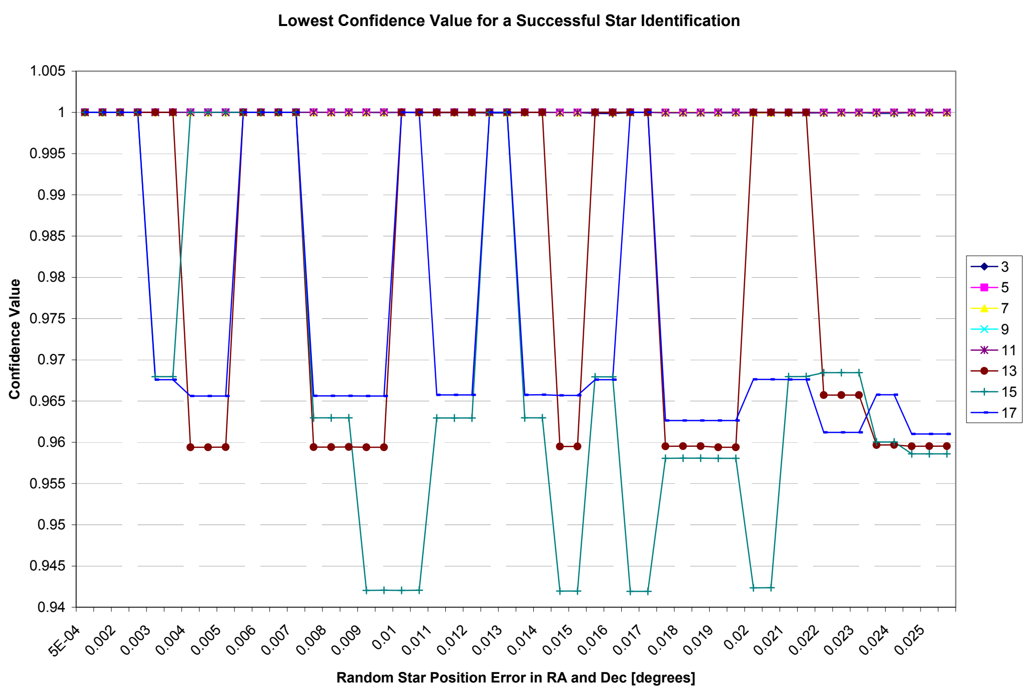

Figure 7 Lowest Probability Value for a Successful Star Identification

Successful star identification probability values are desired to be high so that they are easily distinguishable from failed identifications. Figure 7 illustrates that the smaller the input vector length, the higher the successful identification probability value. This is in contrast with the previous figure which illustrated that the longer input feature vector was favourable. To get a clearer picture of the optimal choice for feature vector length, the difference between the highest failure and the lowest successful identification confidence value must be examined.

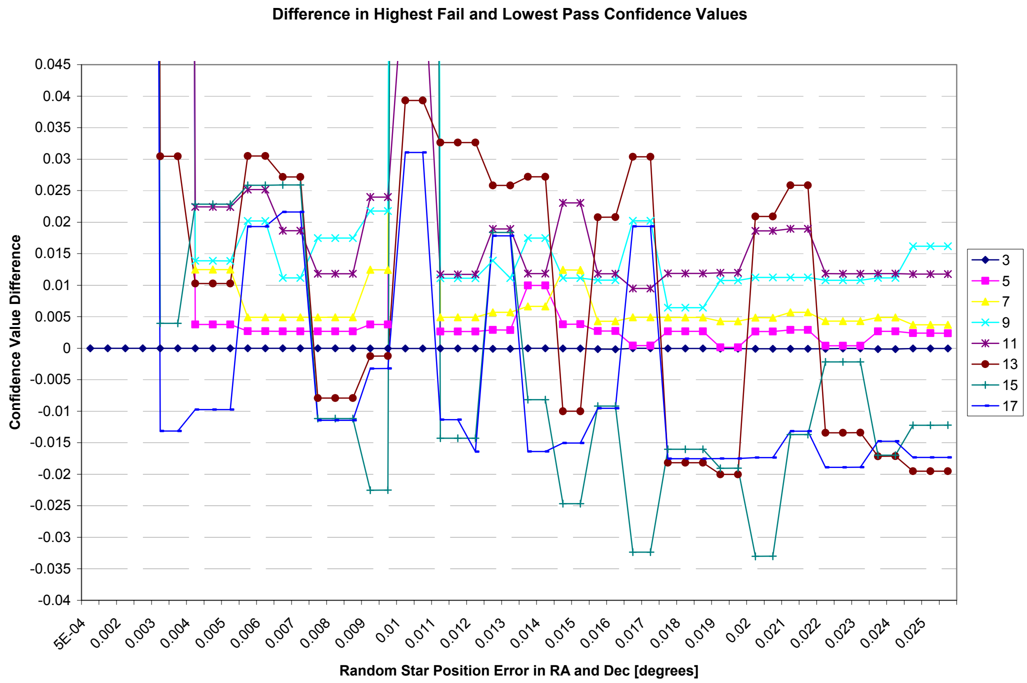

Figure 8 Difference in Highest Fail and Lowest Pass Probability Values

Further analysis of the highest fail and lowest pass probability value is shown in Fig. 8. Consistently positive values allow for a reliable prediction of successful star identifications with no rejection of successful identifications because their probability value is below the acceptance limit. In this case, the probability value limit is set just above the highest failing probability value. If any negative values are present then there are wasted successful identifications. This makes the input feature vectors of length, 17, 15 and 13 unacceptable for this application. The smaller the input feature vector, the smaller the buffer between the highest fail and lowest pass probability value. This equates to having to be more accurate with the choice of an acceptance probability level for the smaller input feature vectors. This effect is to such an extent that the input feature vectors of length 3 and 5 do not provide enough of a buffer to be reliably used.

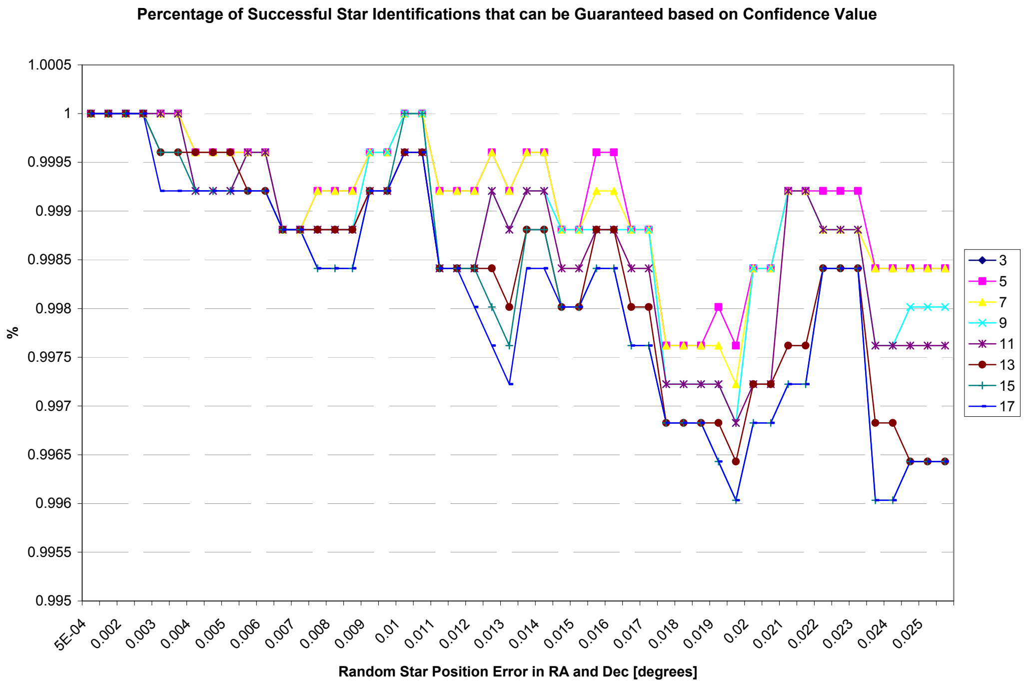

Figure 9 Percentage of Successful Star Identifications that can be Guaranteed based on Probability Value

The percentage of successful star identifications that have a probability value which is above the highest failing probability value is illustrated in Fig. 9. An input feature vector with length 3 is not visible as it lies on the zero line meaning that 100% the successful identifications can not be distinguished from failed identifications. For the input feature vectors apart from length 3, the shorter the input feature vector, the higher the percentage of guaranteed successes. All vector lengths except 3 have usable success rates in excess of 99.6% for the simulated conditions.

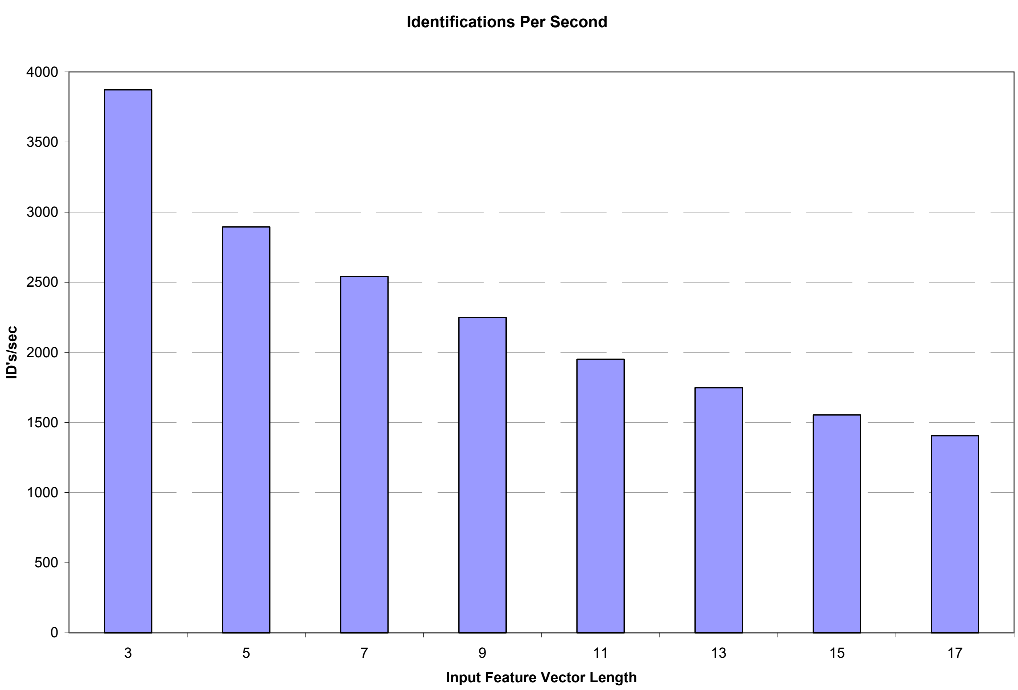

Figure 10 Identifications per Second

Calculation of the processing time of the CPN implementation was undertaken on a Pentium M 1.6GHz personal computer running windows XP with the results illustrated in Fig. 10. The processing time, although calculated in an environment not representative of the final system that it will be implemented into, gives an idea of the processor load and difference between the varying input feature vector lengths.

Discussion

The input feature vector length is the key variable and it affects the performance of the system substantially. Vector lengths of 3, 5, 13, 15 and 17 have to be ruled inappropriate due to the insufficient buffer between their highest failed probability value and the lowest successful identification probability value. This leaves lengths of 7, 9 and 11 that make suitable candidates. A rating against each other on the key performance criteria is illustrated in Table 2.

Table 2 Simulation Flight Parameters

Rating	Probability Level Leeway	Computation Efficiency	Usable Success Rate	Stars Needed
Best	11	7	7	7
Medium	9	9	9	9
Worst	7	11	11	11

Based on the information in Table 2, an input feature vector of length 7 proves to be the best in all performance criteria except the leeway in choosing the acceptance probability value. The acceptance probability level is crucial to the reliable operation of the system, too high and successful identifications will be rejected, too low and false identifications will be accepted. In-field rather than simulated testing will determine if the narrow acceptance probability level leeway of the input feature vector of length 7 is suitable.

The simulations were conducted with test data that had capped random error in stars for the Right Ascension (RA) and Declination (Dec) ranging from 0.0005 to 0.025 degrees. Error introduced in the star positions from the quantisation in the CCD is up to 0.0045 degrees. The majority of other errors are generally common to the whole image plane so they are assumed to be minor in comparison. This in mind, and doubling the CCD quantisation error to 0.009 degrees to cover the neglected and unknown errors, returns a usable success rate of 99.96%.

VI. Conclusion

The star identification method described in this paper provides an accurate and fast method for reliably identifying stars. With the correct choice for the acceptance probability value, values approaching 100% accuracy can be achieved. Successful star identifications were made on more than 99.6% of all the test data using the three acceptable input feature vector lengths of 7, 9 and 11.

Acknowledgments

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