Introducing dead bands within two-dimensional clusters of user data to improve data classification

David Adrian Sanders
School of Engineering,
University of Portsmouth,
Anglesea Road Building,
Portsmouth, PO1 3DJ, UK
david.sanders@port.ac.uk

Alexander Gegov
School of Computing,
University of Portsmouth,
Buckingham Building in Lion Terrace,
Portsmouth, PO1 3DJ, UK
alexander.gegov@port.ac.uk

Jorge Bergasa-Suso
FriendShake Ltd and Kiticow Ltd,
Innovation Space in Halpern House,
1 Hampshire Terrace,
Portsmouth, PO1 2QF, UK,
jorge.bergasa@gmail.com

Simon Chester
School of Engineering,
University of Portsmouth,
Anglesea Road Building,
Portsmouth, PO1 3DJ, UK,
simon.chester@port.ac.uk

Rinat Khusainov
School of Engineering
University of Portsmouth,
Anglesea Road Building,
Portsmouth, PO1 3DJ, UK
rinat.khusainov@port.ac.uk

Nils Bausch
School of Engineering
University of Portsmouth,
Anglesea Road Building,
Portsmouth, PO1 3DJ, UK
Nils.Bausch@port.ac.uk

Abstract—**Methods are described to create more accurate sub sets of user data by introducing dead bands into data clusters. User data is collected and then mined. That produces clusters of data. Dead bands are then generated to delineate and describe the data in the clusters more accurately. This is accomplished by classifying data inside the newly created dead bands as NOT being in either of two or more clusters. For example, three clusters are generated from two. If the two were YES and NO then another set of DON'T KNOW is introduced. The new set improves the precision of choices made using data in the YES and the NO clusters. Dead bands are introduced by establishing a radius from the corners of 2-D shapes containing the clusters or by establishing a horizontal or vertical line in parallel with the edges. Each radius or edge encompasses 80% of user data nearest to the corner or edge of the data set. 20% are outside and excluded from their original set. If lines do not overlap, then a dead-band is created to contain user data that is not as confident. That increases the likelihood of accurate decisions being made about the new sets of user data. Case studies are described to demonstrate that.**

Keywords—user information; post processing; clusters; data; mining; dead bands; set.

I. INTRODUCTION

This paper describes recent advances in improving the identification of accurate sub-sets by post processing the outputs from data mining systems. The data mining identifies rules for separating data. The new methods then improve on those results by automatically creating dead bands to refine the data clusters. This is accomplished by classifying data inside the new dead bands as being outside of the original clusters. If there were two clusters that were categorically YES and categorically NO then a new third cluster is created that is DON'T KNOW. The establishment of a new set enhanced the correctness of choices made about data within the new remaining YES and NO clusters. Case studies are described as illustrations of that:

FIRST STUDY – Records the way in which users interact with WWW pages on the internet and with computer interfaces and then infers the learning style of the user from that data.

SECOND STUDY - Monitors the way in which remote users interact with a WWW site and predicts whether they will convert to a potential customer.

The remainder of the paper considers the Felder-Silverman index before describing some case studies and the creation and testing of the patterns used to describe user interface activity. Results and discussion are presented.

II. Felder-Solomon Index of Learning Styles

The way that an individual attains, remembers, and recalls information is called their learning style. People learn in a variety of different ways. They see things, hear things, reflect about what they have seen and heard and act on that reflection. They reason logically and / or use intuition, they memorize facts and / or visualize [1,2].

A number of widespread learning styles are tactual, visual, auditory and kinaesthetic. Auditory learners prefer spoken directions and like to listen. Visual learners like seeing the body language and expression of the person teaching them. They distinguish words by sight but can be distracted by movements or actions. Tactual learners prefer drawing or doodling to help them to remember they perform well when they are allowed to take down their own notes in classes. kinaesthetic learners prefer taking part in activities and learn best if their s movement. Various tools have been used to identify these different styles of learning.

Students can have differing attitudes towards teaching and learning, diverse amounts of motivation, and will respond differently to different classroom surroundings, atmospheres, circumstances and practices. The more that someone understands these differences, the better they can help people learn [3].

Learning style is derived from psychological concepts. Learning styles are defined as "*characteristic cognitive, affective, and psychological behaviours that serve as relatively stable indicators of how learners perceive, interact with, and respond to the learning environment*" [3]. Various models of learning styles have been suggested in the literature, for example: Dunn and Dunn; VARK; Delineator; ILS; Gregorc and Kolb. Tools have been developed for these models and they can be used to assess learning styles.

VARK stands for Visual, Aural, Read/Write and Kinaesthetic and was developed from earlier neuro-linguistic models. It is a sensory model [4]. Learning styles are defined in [4] as "*an individual's characteristics and preferred ways of gathering, organizing, and thinking about information*". VARK considers perceptual modes and focuses on the way that people take in and give out information and individuals have different personal preferences for each perceptual mode but they can also perform within other modes [5]. A free questionnaire is available from www.vark-learn.com.

The Felder and Silverman Index of Learning Styles [6] originated in engineering and defines learning style as "*the characteristic strengths and preferences in the ways individuals take in and process information*". Felder said that people have individual preferences along five bipolar continua: Active / Reflective; Sensing / Intuitive; Verbal / Visual; Sequential / Global; and Intuitive / Deductive.

The Index of Learning Styles is a free questionnaire available from www.ncsu.edu/effective teaching. People choose endings to sentences that focuses on different aspects of learning.

Active learners prefer doing, especially within groups. Reflective learners prefer working by themselves and reflecting about a task before doing anything. Sensing learners prefer data, facts and testing and like detail. Intuiting learners like dealing with theories and ideas, especially if they can comprehend innovative new ideas. Verbal learners prefer hearing about information and like discussing a subject. Visual learners prefer pictures, words, symbols, diagrams, charts and reading. Sequential learners like linear reasoning and predictable procedures. Global learners like integration and synthesis, making intuitive connections and discoveries to understand complete systems and patterns [5]. Teaching approaches are discussed in [6] that are useful to matching learning preferences emerging from the Index of Learning Styles as shown in Fig. 1 (reproduced from [2]).

Active learners prefer to try things out, doing and seeing what works and what does not, especially with other people. Reflective learners like to think first and to take notes and work by themselves. Intuitions prefer discovery, new concepts and abstraction. Visual learners like pictures, diagrams, films, and demonstrations. Verbal learners prefer to hear and to discuss things, they like to tape lectures, and explain things to themselves. Sequential learners prefer moving step-by-step towards a solution. Global learners like a big picture, taking in random information before laying it all together at the same time. They often work intuitively [5].

The Kolb learning style is an experiential model, which defines learning as "*the process whereby knowledge is created through the transformation of experience*". Learning is a continuous set of processes, with less emphasis on the final outcome. The model suggests using a 4 x mode learning cycle of: Concrete Experience; Reflective Observation; Abstract Conceptualization; and Active Styles.

Complementary learning styles	
Sensing	*Intuitive*
- Draws on physical sensation	- Draws on insight
- Practical and observing	- Imaginative and interpretive
- Prefer the concrete: facts and data	- Prefer the abstract: theory and modelling
- Prefer repetition	- Prefer variation
Visual	*Verbal*
- 'Show me how'	- 'Tell me how'
- Prefer pictures and diagrams	- Prefer written and spoken explanations
Active	*Reflective*
- 'Let's try it out'	- 'Let's think it through'
- Process information by physical activity	- Process information introspectively
- Learn by working with others	- Learn by working alone or in pairs
Sequential	*Global*
- Understand in continual and incremental steps	- Understand in large leaps
- Linear reasoning process	- Tacit reasoning process
- Convergent thinking and analysis	- System thinking and synthesis

Fig. 1. Learning preferences emerging from learning styles

Some systems have considered perception [7] and intelligent Web-based and other software systems have attempted to adapt in order to match user learning styles [8]. That adaption has depended on identifying learning style(s). They have tended to use questionnaires in order to assess learning styles, and systems like iWeaver adapt to preferences by monitoring patterns of navigation and through user feedback. No systems have managed to successfully infer learning styles from an analysis of the way in which a user interacts with a computer and navigates thorough a WWW site.

Felder-Silverman dimensions were picked out for detailed investigation of learning styles before writing the software for the work described in this paper as it postulated 4 learning style dimensions that could be determined from user data extracted form observing a user interacting with their computer system: timing, action, location, etc.

III. FIRST CASE STUDY

Learning styles of volunteers were initially determined by questionnaire so that they could be tested against styles that were automatically calculated. They were automatically calculated by an agent considering the way that a user interacted with their user interface. An action detector decided if a user was taking part by checking the time since the last activity on the user interface.

To automatically establish a learning style for a user, relationships were sought out concerning how various users with various learning styles used the Internet and the user interface. In addition, relationships were sought out between the arrangement and the elements of WWW pages that were preferred by users with different learning styles. A number of different versions of learning styles were studied [9, 10]. The Felder-Silverman Reflective / Active dimensions are used as examples. Active learners prefer doing, for example modelling or talking about a topic. Reflective learners like to consider and reflect about things quietly before taking action.

IV. CREATING AND TESTING PATTERNS

Experiments were conducted to seek out rules about user interface activity and about the features and appearance of a WWW page that could foretell the learning style of a human user. The rules were to be founded on user behaviour while they browsed the WWW and internet. The activity at the user interface was recorded while users completed tasks. The activity of the user and structure of the WWW pages were examined and logged every time a user visited a page. A database was set up and data about a user was labelled with the predicted dimensions of that user. They were also signposted to the predicted user dimensions from standard questionnaires about learning style. That allowed data mining to take place to contrast and compare. These are the factors that were logged by a software agent:

Time spent within a WWW page.
Speed of mouse movement.
Distance the mouse moved.
Distance the mouse moved in the X and Y axis;
Speed of scrolling.
Distance scrolled.
Number of times a menu was used.
Number and amount of changes in scroll direction.
Use of the back button.
Use of the forward buttons.
Amount and type of data copied.
Amount of data dragged.

The parameters concerning the structure of the WWW pages that were logged are:

Length of text on a page.
Area and number of images.
Ratio of images to text.
Existence and position of tables.
Numbered and bulleted lists.
Existence of sound files.
Existence of video files.
Animations on a page.
ActiveX components on a page.
Existence and location of question marks.
Number of words.
Keywords, for example: "example," "figure," "question" and "diagram."

Sixty seven users took standard surveys to identify their learning styles. Of these, twenty users were observed and data logged in order to test the methods and the systems and to learn about some simple potential correlations. Then twenty four different users with various learning styles used Internet Explorer to investigate a topic for 20 minutes. The software agent logged their activity and users rated WWW pages to say how well they understood a page. Data collected from the users and data collected by the software agent were examined to find relationships and connections between: learning style dimension, user interface activity, and the content of pages the users thought were useful and easy to understand. Some relationships and connections were found between learning style dimensions and the way a user interacted with their user interface and the content of the WWW pages they visited. The twenty most significant parameters for predicting each of the dimensions were obtained from PolyAnalyst, a Data Mining tool [8]. The 5 x most noteworthy parameters in predicting whether a user was an Active or a Reflective learner are listed here:

$$1)\ \frac{\text{Area of images}}{\text{Text length} \times \text{Scroll direction changes}}$$

2) Average time spent on page

$$3)\ \frac{\text{Area of images}}{\text{Text length} \times \text{Time spent in page}}$$

$$4)\ \frac{\text{Area of images}}{\text{Text length} \times \text{Scroll distance}}$$

$$5)\ \frac{\text{Image count}}{\text{Text length} \times \text{Mouse distance in Y axis}}$$

These generated relationships and the dimensions that were already noted for each individual user were exploited to generate a model to predict learning style for new users. The model generated a level of confidence that a user fitted into one of the extremities of a dimension of learning style.

To examine the helpfulness of the classification, another group of eight users were given the identical brief. The agent logged their activity and the WWW data. The information was presented to the model, and the model predicted the dimension for every user. Users were also asked to complete an Index of Learning Styles Questionnaire. The results from the models were compared with the results from the Index of Learning Styles Questionnaire for each user [10].

A method used in [11] was similar and the prediction made about active and reflective learning styles was only a little better than a naive guess. Nevertheless, that research was an initial success despite the results being somewhat naïve. It spawned the idea of this work that was first described in [12].

In this research, results from an Index of Learning Styles Questionnaire were recorded in a database so that the favoured learning styles for the users were known before they took part in the experiments. The average spread of the learning dimensions across the sample population is shown in Table I.

Table I: Distribution of dimensions of learning style over sample population

Dimension	Number of people	%
Actives	38	57%
Reflectives	29	43%

The lowest precision needed for the rules to be successful was extracted from Table I. A simple guessing strategy that assumed all the users were Active would be 57% accurate. Any rules discovered to forecast a learning dimension needed to be better than the naive guessing strategy.

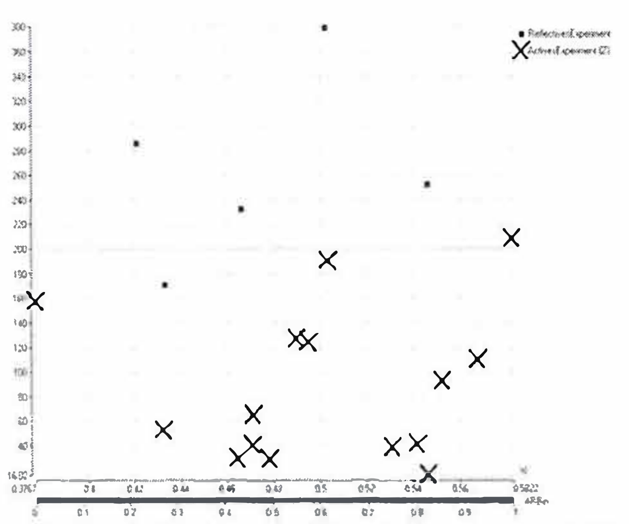

Fig 2: A plot of user data points of "Amount of mouse movement in Y" on the X axis and the "ratio of images to text length AND distance scrolled" on the Y axis showing clusters of Reflective users (square) and Active users (crosses).

Tests took place to differentiate between: Sensing OR Intuitive; Visual OR Verbal; and Sequential OR Global. Results were no better than a naive guess. The new methods presented here, improve on these results by creating new sets of DON'T KNOW in addition to YES or NO (or Sequential OR Global) for parameters that are considered to be significant. Fig. 2 is a scatter graph that shows some results from 20 users. Several scatter graphs were usually used at the same time and in multiple dimensions but for ease of representation, Fig. 2 just shows a single scatter graph in two dimensions; in this case showing a cluster of Reflective (square) and a cluster of Active (cross).

In Fig. 2, the squares and crosses overlap so that it is difficult to draw any significant line that could split up the two sorts of data into completely separate clusters.

That problem was identified in [12]. Users were forced into the set of Reflective Users OR into the set of Active Users. Each of the sets of parameters made decisions about each of the learning dimensions, and the likelihood of a user belonging to either of the dimensions was calculated from those decisions. This worked well for users who were definitely within one category for all of the decisions, but most of the users only had a tendency towards one dimension or another, and that tendency sometimes changed depending on their circumstances or mood. Dead bands were introduced into each set of two-dimensional clusters to define a new set where a user did not belong to either dimension. That was similar to work described in [12, 13]. This was accomplished by either establishing a straight line boundary (Fig. 3, Fig. 4) or by establishing a radius (Fig. 5, Fig. 6).

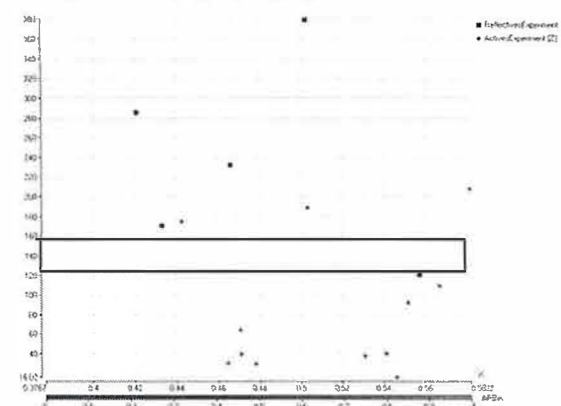

Fig. 3: A 2-D dead band created with straight lines for 2 sets of user attributes.

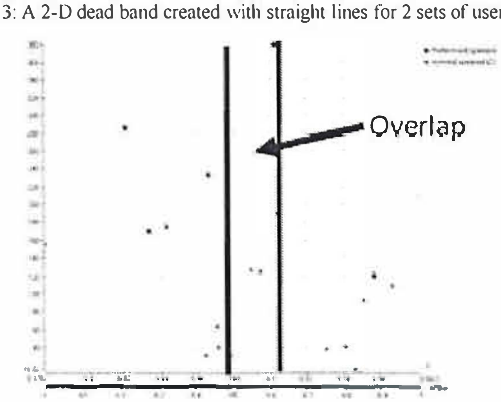

Fig. 4: An overlap shown for two sets of user attributes in 2-D.

Each line (or radius) was determined during learning bearing in mind the 2-D position of each user within each dimension cluster. A radius (or line) was inserted so that 80% of users were within a particular dimension nearest the edge (or origin). The remaining 20% were beyond the line (or radius) and were recorded as NOT being in the set. If the lines didn't overlap, then dead bands could be created to contain users that had less certain results.

Fig. 3 and Fig. 5 both have a dead band shown by the shaded area. That band signified a new unknown UNKNOWN set.

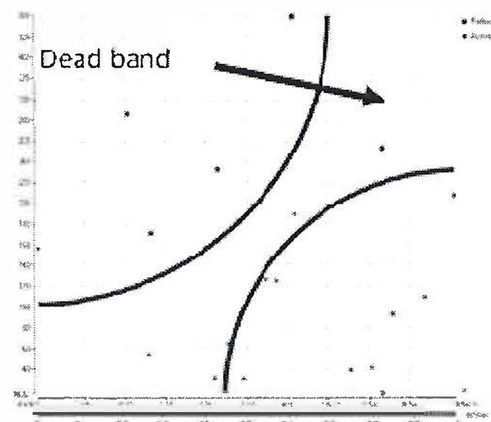

Fig 5: Dead band created with curves for two sets of user attributes in 2-D.

Now, users could be characterized as Active, Reflective or Unknown. Fig. 4 and Fig. 6 do not have a dead band, because each 80% line overlaps with the other.

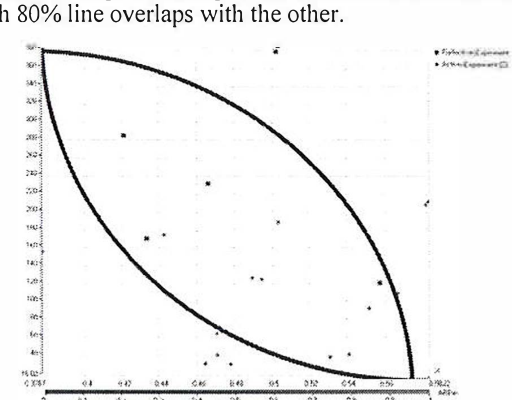

Fig 6: A curved overlap shown for two sets of user attributes in 2-D.

If more than one dead band was created then a choice needed to be made between the sets of data with each dead band. In that situation, the widest dead band was selected. So in this case, Fig. 5 shows the sets for Active / Reflective user dimensions employing the "*Amount of mouse movement in Y*" (X axis) and "*Ratio of area of images to length of document AND distance scrolled*" (Y axis). The option shown in Fig. 5 was selected because space between the lines was bigger than the space between the straight lines. The algorithm to insert dead bands is in [12].

Reflective, Active and the new "Unknown" set were used in this work. Users were classified as perhaps Active or perhaps Reflective for every parameter pair if outside of the dead band and definitely inside a set bounded by the new lines introduced to segment the clusters. The effect was to remove cases that were less certain from the pairs of individual user data so that when results were classified, they were more positive and not as naïve.

V. TESTING FOR THE FIRST CASE STUDY

The new method had a meaningful outcome. The Active/Reflective results are shown in Table II. Using this new method, some users were sometimes not defined by the system, because they always fell into the unknown set for every pair of useful parameters (less than 10%).

Table II: Accuracy achieved after dead bands were introduced compared with the naïve predicted accuracy.

	Accuracy with Dead Bands	Naïve pred. Accuracy
Active/ Reflective	80%	58%

Table II shows an improvement over [11] which only achieved 71% over 57%. Accuracy in deciding if a user was Reflective or Active significantly improved. 81%. were classified correctly for the Reflective / Active user dimension. An improvement compared to 71%.

VI. TESTING FOR THE SECOND CASE STUDY

A second case study attempted to predict whether a visitor to a WWW Site would convert to a potential customer by monitoring their user behaviour. Tests were undertaken to unearth rules about activity within test WWW Sites and about the features of the WWW pages that might forecast if a visitor to the WWW site would turn into a likely customer. A likely customer was described as a visitor to the WWW site who made contact with the company hosting the site by email from within the site.

Data was logged and later analyzed. A software agent recorded page use while a user investigated the test sites. User activity and page structure were analyzed and logged every time a page was visited. These were then labelled with the result from the user, did they leave the site or did they became a potential customer? The data from all the users was then data mined. Parameters logged by the agent were similar to those used in Case Study One and included: time within a WWW page; use of forward and back buttons etc. Page structure parameters were also logged, such as: amount of text; number of images, area of images; ratio of images to text, location (and presence) of tables, numbered and bulleted lists, presence of video and sound files, animations and ActiveX components.

The data was collected and then analysed to find correlations between: the way information was presented in visited pages, human computer interaction and customer conversion. The twenty parameters that were most significant in predicting likely customers were extracted but unfortunately the significant parameters are held commercially in confidence.

The parameters and the user values were then used to create a probability model for each result (converting to a likely customer or not). That could predict likely conversion of new users based on values of parameters recorded by the software agent. The model generated a level of certainty that a customer belonged within the extremes of one of the two potential results. Data from activity by 795 users were tested. Activity was logged by the software agent and entered into the model. The model returned a predicted result for every user and the results were compared with results predicted by the models.

VI. RESUTS FOR THE SECOND CASE STUDY

A significant improvement was again made when the additional set was included, adding UNKNOWN for every ach pair of sets. The effect is shown in Tables III, IV and V.

Table III: Distribution of dimensions of learning style over sample population.

Dimension	Number of users	%
Convert	450	57%
Leave	340	43%

A small number of users were not defined by the system, because they were in UNKNOWN sets for almost every pair of parameters. At first, the results for leave / likely customer were only the same as guessing (Table IV).

Table IV: Accuracy of models without dead bands. Left = Accuracy achieved, and Right = naïve predicted accuracy to be reached before results could be considered significant.

	Accuracy	Naïve pred. Accuracy
Convert / Leave	59%	57%

Introducing the dead bands improved the results and Table V shows an improvement over the results shown in Table IV.

Table V: Accuracy of models with dead bands. Left = Accuracy achieved after introducing dead bands, and Right = Accuracy of models without dead bands.

	Accuracy with Dead Bands	Accuracy without Dead Bands
Convert / Leave	69%	59%

VII. DISCUSSION AND FUTURE WORK

Inserting the new UNKNOWN set generated rules that were more accurate.

The work used a keyboard and mouse but on-going research is experimenting with different sensors [14,15] and user interfaces [16,17] such as joysticks [18-23] and the use of AI is being trialed [24-32], using Blackboard systems [33, 34], ANNs [35-37] and fuzzy systems [38-41] with a view to improving the gathering of user data and identification of correlations between relevance ratings for WWW pages and their actual perceived usefulness. The methods are also being introduced to a simulation based robot command library [42].

More accurate classification rules would improve the usefulness of the system to improve the support given to users with particular learning styles (reflective or active) or to identify more likely customers. Research so far has assumed that customer objectives and learning styles remain the same, but learning styles are not completely distinctive and the model validity for both has been questioned occasionally in the literature. The current work is starting to investigate using thresholds within the algorithms for calculating learning styles. Future work will test more users to further verify the measurements. In addition, the algorithms rely on parameters to control the banding (the 20/80 split). Future work will investigate approaches for tuning these parameters as they can influence the effectiveness of the proposed approach.

REFERENCES

[1] R. Felder, "Learning & Teaching Styles in Foreign & Second Language Education". Foreign Language Annals, vol 28 (1), pp. 21-31. 1995.

[2] M. Heenaye, B. A.Gobin, N. A. M. Khan , "Analysis of Felder-Solomon Index of Learning Styles of Students from Management andEngineering at the University of Mauritius". Journal of Education and Vocational Research, vol. 3 (8), pp. 244-249, 2012.

[3] R. Felder and R. Brent, "Understanding Student Differences". Journal of Engineering Education, 94 (1),5 pp. 7-72. 2005.

[4] N. D. Fleming, "Teaching and learning styles: VARK strategies". Christchurch, New Zealand: 2001.

[5] T. F. Hawk and A. J. Shah, "Using Learning Style Instruments to Enhance Student Learning". The Decision Sciences Journal of Innovative Education, 5 (1) pp. 1-19, 2007.

[6] R. M. Felder, and L. K. Silverman, "Learning styles and teaching styles in engineering education". Eng Ed, 78 (7), pp. 674–681. 1988.

[7] D.A. Sanders, "Perception in robotics". IND ROBOT vol. 26 (2), pp. 90-92. 1999.

[8] J. Bergasa-Suso, "Intelligent software agents for teaching across the WWW", PhD, Portsmouth, 2005.

[9] T, Litzinger, S. Lee, andJ. Wise, et al, "A psychometric study of the Index of Learning Styles". J. Eng Ed vol. 96, no. 4, pp. 309-319. 2007.

[10] R. Felder, and B. Soloman, "Index of Learning Styles Questionnaire" [Online]: http://www.engr.ncsu.edu/learningstyles/ilsWeb.html. 2009.

[11] J. Bergasa-Suso, D. A. Sanders and G.E. Tewkesbury, "Intelligent Browser-Based Systems to Assist Internet Users". IEEE Transactions on Education, vol. 48 (4), pp. 234 – 240. 2005.

[12] D. A. Sanders and J. Bergasa-Suso, "Inferring Learning Style from the Way Students Interact with a Computer User Interface and the WWW". IEEE Transactions on Education vol. 53 (4) , pp. 613-620. 2010.

[13] A. Hess, R. Khoussainov and N. Kushmerick, "Ensemble Learning with Biased Classifiers: The Triskel Algorithm", Lecture Notes in Computer Science, vol. 3541, Springer-Verlag. pp. 226-235.

[14] D.A. Sanders, Environmental sensors and networks of sensor. SENSOR REV vol. 28 (4), pp. 273-274. 2008.

[15] D. C. Robinson, D. A. Sanders, and E. Mazharsolook, "Sensor-based ambient intelligence for optimal energy efficiency". SENSOR REV vol. 34 (2), pp. 170-181. 2014.

[16] D. Sanders, G. Tewkesbury, A pointer device for TFT display screens that determines position by detecting colours on the display using a colour sensor and an Artificial Neural Network. DISPLAYS vol. 30 (2), pp. 84-96. 2009.

[17] D. Sanders, S. Urwin-Wright, G.E. Tewkesbury. Pointer device for thin-film transistor and cathode ray tube computer screens. ELECTRON LETT vol. 41 (16), pp. 894-896. 2005

[18] D. A.Sanders, Controlling the direction of "walkie" type forklifts and pallet jacks on sloping ground. ASSEMBLY AUTOM vol. 28 (4), pp. 317-324. 2008.

[19] D. Sanders, I. Stott, A new prototype intelligent mobility system to assist powered wheelchair users IND ROBOT vol. 26 (6), pp. 466-475. 1999.

[20] D.A. Sanders and A. Baldwin, A X-by-wire technology. Total Vehicle Technology Conference, pp. 3-12 Year: 2001.

[21] D.A Sanders, N. Bausch, H. Liu, *et al*, Improving Steering of a Powered Wheelchair Using an Expert System to Interpret Hand Tremor, in Proc' of Intelligent Robotics & Apps (ICIRA), vol. 9245, pp. 460-471. 2015.

[22] D. Sanders, I. Stott, J. Graham-Jones, *et al*, Expert system to interpret hand tremor and provide joystick position signals for powered wheelchairs with ultrasonic sensor systems, IND ROBOT vol. 38 (6) pp. 585-598. 2011.

[23] D.A. Sanders, I. Stott, D. Robinson, *et al*, Analysis of successes and failures with a tele-operated mobile robot in various modes of operation, Robotica vol. 30, pp. 973-988. 2012.

[24] D.A. Sanders, Progress in machine intelligence. IND ROBOT vol. 35 (6), pp: 485-487. 2008.

[25] D. Sanders, "Introducing AI into MEMS can lead us to brain-computer interfaces and super-human intelligence". ASSEMBLY AUTOM vol. 29 (4), pp: 309-312. 2009.

[26] D.A. Sanders and A. Gegov, "AI tools for use in assembly automation and some examples of recent applications". ASSEMBLY AUTOM vol. 33 (2), pp: 184-194. 2013.

[27] D.C. Robinson, D. A. Sanders and E. Mazharsolook, "Ambient intelligence for optimal manufacturing and energy efficiency". ASSEMBLY AUTOM vol. 35 (3), pp: 234-248. 2015.

[28] D.A. Sanders, Y.C. Tan, I. ROGERS, *et al*, An expert system for automatic design-for-assembly. ASSEMBLY AUTOM vol. 29 (4), pp. 378-388. 2009.

[29] D. Sanders, G Tewkesbury, A. Gegov, *et al*, Fast transformations to provide simple geometric models of moving objects. In Proc' Intelligent Robotics & Applications (ICARA), Pt I vol. 9244, pp. 604-615. 2015.

[30] D.A. Sanders, G.E. Tewkesbury, D. Ndzi, *et al*, Improving automatic robotic welding in shipbuilding through the introduction of a corner-finding algorithm to help recognise shipbuilding parts, Journal of Marine Science and Technology vol. 17 (2), pp. 231-238. 2012.

[31] D.A. Sanders, G.E. Tewkesbury, I.J. Stott, *et al*, Simple expert systems to improve an ultrasonic sensor-system for a tele-operated mobile-robot, SENSOR REV vol. 31 (3), pp. 246-260. 2011.

[32] D.A. Sanders, G. Lambert, J. Graham-Jones, *et al*, A robotic welding system using image processing techniques and a CAD model to provide information to a multi-intelligent decision module. ASSEMBLY AUTOM vol. 30 (4), pp. 323-332. 2010.

[33] D. A. Sanders, amnd A. D. Hudson, "A specific blackboard expert system to simulate and automate the design of high recirculation airlift reactors". MATH COMPUT SIMULAT vol. 53 (1-2), pp. 41-65. 1999.

[34] D.A. Sanders, A. D. and G.E. Tewkesbury *et al*, "Automating the design of high-recirculation airlift reactors using a blackboard framework". Expert systems with applications vol. 18 (3), pp: 231-245. 2000.

[35] S. Erwin-Wright, D. Sanders, and S. Chen, "Predicting terrain contours using a feed-forward neural network". Engineering Applications of Artificial Intelligence vol. 16 (5-6), pp: 465-472. 2003.

[36] D. A. Sanders, "Recognizing shipbuilding parts using artificial neural networks and Fourier descriptors", Proc of Inst of Mechanical Engineers Part B-Journal of Eng Manufacture vol. 223 (3), pp: 337-342. 2009.

[37] D.A. Sanders, B.P Haynes, G.E Tewkesbury, *et al*, The addition of neural networks to the inner feedback path in order to improve on the use of pre-trained feed forward estimator, Mathematics and Computers in Simulation, vol. 41 (5-6), pp. 461-472. 1996.

[38] A. Gegov, F. Arabikhan, and D. Sanders, Rule base simplification in fuzzy systems by aggregation of inconsistent rules, Journal of Intelligent & Fuzzy Systems vol. 28 (3), pp. 1331-1343. 2015.

[39] A. Gegov, D. A. Sanders, and B. Vatchova, Complexity management methodology for fuzzy systems with feedback rule bases, Journal of Intelligent & Fuzzy Systems vol. 26 (1), pp. 451-464. 2014.

[40] A. Gegov, N. Gobalakrishnan, D. Sanders, Filtration of Non-Monotonic Rules for Fuzzy Rule Base Compression. Int Journal of Computational Intelligence Systems,vol. 7 (2), pp. 382-400. 2014.

[41] A. Gegov, N. Gobalakrishnan, D. Sanders, Rule base compression in fuzzy systems by filtration of non-monotonic rules. Journal of Intelligent & Fuzzy Systems, vol. 27 (4), pp. 2029-2043. 2014.

[42] G. Tewkesbury & D. Sanders, A new simulation based robot command library applied to 3 robots. Jrnl Rob Syst vol. 16 (8) pp. 461-469. 1999.