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1 3-D Facial Landmark Localisation

This topic explores a method for automatic localization of facial landmarks where an algorithm generates a set of candidate locations from feature detectors and performs a combinatorial search constrained by a flexible shape model. The application for this research are in the field of biometric identification and medicine. In the field of medicine such applications are facial surgery (Sharifi, 2008), lip movement assessment (Popat, 2013) or cranial facial dysmorphology. It is stated in the paper that with the increased use of 3-D scanners the possibility to overcome traditional limitations of 2-D scanners have become discovered. However according to Phillips current 3-D scanners suffer from two shortcomings: 1) not all 3-D scanners provide texture and, even when they do it cannot be assured that it is accurately registered to the geometry. 2) they may become more sensitive to view point and lighting conditions, where texture information is not invariant to these factors. (Phillips, 2005) In the presence of obstacles obstructing landmarks, for example, scarf or jacket in the way of a chin the use of shape regression with incomplete local features (SRILF) was used for the detection of such facial landmarks. SRILF handles any combination of missing points and allows for nonrigid deformations. SRILF algorithm has three components: 1) selection of candidates through local feature detection; 2) partial set matching to infer missing landmarks by regression; and 3) combinatorial search which integrates the other two components. Local feature detection is described by a set of vertices in M where M is a facial surface described by the V vertices. Then a set of 3-D annotations containing L landmarks are used to train a local descriptor model for each landmark. The goal is to compute a similarity score $s(v)$ based on the local descriptors, that correlates well with the correct position of the targeted landmark. The second step is Partial set matching using statistical shape models. A

shape vector is constructed by concatenating the coordinates of L landmarks. The goal is to infer the coordinates of landmarks using principle component analysis over a FRGC (Facial Recognition Grand Challenge) training set. Combinational feature matching and the use of RANSAC is a matching procedure where L sets of candidate points for each landmark have a set of top scoring vertices which were determined during training period and then evaluated. The SRILF algorithm is described in the paper as follows: Start with the mesh M , for all the landmarks compute the descriptor scores, determine the landmark candidates. Next for all combinations of candidates obtain the best candidates within M . Keep iterating the subset until it achieves the desired highest score and then evaluate the geometry. In conclusion, the algorithm generates sets of candidate points from geometric cues extracted by using the APSC descriptors and then performs a combinatorial search using a constrained flexible shape model. In the scenario where a landmark was not accurately detectable the use of partial subsets of landmarks were taken to make an inference on the missing landmark. After Evaluating the facial recognition grand challenge data, errors in the ranges of approximately 3.5 mm were obtained. Such an accuracy is amazing. It is apparent that the trained data sets using artificial intelligent techniques were used but the type of technique was not stated in the paper. However in this example, applied artificial intelligence was definitely applicable in transactions systems of facial recognition.

2 Filtering Reviews by Random Individual Error

This paper tackles the problem of physician ratings websites by determining the quality of information extracted by applying artificial intelligence to detect the random individual error within the reviews. The paper goes on to describe the challenges as (1) the content and sentiment analysis of the review texts and (2) the removal of the random individual error contained in them (Michaela, Frederik, Sabine, & Valentina, 2015). To tackle these problems these researchers assigned polarities to automatically recognise opinion phrases in reviews and then check for any divergence in the rating and text. Application of this research paper aids in the current increase in fraudulent internet reviews. This is a big issue particularly in online retail, and has attracted attention in recent years from businesses and research community (Mukherjee, Venkataraman, Liu, & Glance, 2013). In some cases reviews were biased and or genuine and may appear to be deceptive which made detection of such reviews difficult in the paper. The data set used was a set of ready-made corpora physician reviews from sites such as jamede.de and docinsider.de. The paper then describes how they detect the random individual errors in the reviews by "divergent polarities" broken into 5 categories assurance, reliability, responsiveness, tangibility and time. For example some polarities can be deduced in a rate my professor situation, where a student will use words such as bad, good or incompetent too much work etc. These words can be correlated as divergent polarities. However some contradictions may occur when the review may be overall satisfactory and based on past experiences and or trust. Machine learning cannot be applied to this scenario but the approach of the application of A.I in this paper is data processing of language and error calculation from the qualitative part in the written review and the quantitative part of the actual valued result. When performing the calculations

the 5 categories are broken into subcategories for each to determine a probability of individual inconsistency in the data sets obtained from the review. Assurance is broken down into trustworthiness, kindness, consideration. Reliability can be broken down into health, education. Responsiveness is sub-categorised into waiting time. Tangibility would have a subcategory of entertainment, and time would be the time taken. In the paper they calculated the divergence of these categories by determining the arithmetic mean for each category based each random individual error per sub category. This is evaluated rate of individual error in reviews depended on the grammar annotated by the person doing the review. Training sets were generated based on this data where they compared true positives as correct and false positive erroneous reviews. They calculated the precision in ratio between true positive and false positive reviews to generate a score to compare with physician reviews. As a result the average precision of each category was 8 percent for assurance, 3 percent for reliability, 50 percent for responsiveness, 28 percent for tangibility and 14 percent for time. What was interesting was the wait time and trust evaluation results were show to be the lowest which makes sense as the data obtained from the review would be difficult to infer from individual error correlated from grammar based analysis.

3 The Regulation of Steam Pressure in a Drum Boiler by Neural Network and System Identification Tech- nique

The application in Artificial intelligence of neural networks is applied to a complex drum boiler system in an attempt to control the output of the system in terms of steam pressure. The inputs of the system are defined as feed water flow rate with respect to heat in order to maintain a desired steam pressure inside the parameters of the boiler. In the paper the ANN method used is a training method based on Levenberg-Marquardt back propagation where the optimal model is obtained by determining the output error using a mean square when the results are filtered. With respect to ANN being applied in similar situations of a complex dynamic system where (Vasickaninova, Bakosova, Meszaros, & Klemes, 2011) used a ANN to evaluate an optimal input for a heat exchanger and compared to a PID controller. The purpose of the Levenberg-Marquardt back-propagation was to account for the non linearity of the system associated with differential evolutions. The back propagation of this type was explored by (Wu & Tsai, 2011) as means to determine the output of a speaker system. All these models have a relationship between input and their respective outputs based on some type of parameters that can be adjusted by a neural network. The model of this experiment is defined by the inputs and outputs of a dynamic system in a differential equation. The ANN algorithm is used solve this boiler non-linear problem by fitting the regression line using a sum of squares error derivation. The neural network ran for

4 Music Emotion Recognition With Standard And Melodic Audio Features

This paper explores the influence of music in the emotions of humans and how this can be studied through datasets of melodies from several songs in an attempt to research a way in searching digital music in a more advanced, flexible way. The purpose of this project is the need for a new technological innovation for the digital era of music. This is due to the increase in demand for more powerful methods of retrieving songs in the context defined by the user. There is several papers related to emotional analysis but it is apparent in this papers perspective that this idea of understanding the emotions invoked from music is a interesting approach in searching for music. There is a current standard for how music is retrieved known as "Music Information Retrieval Evaluation eXchange (MIREX) where the best algorithm used was based on system called a "mood task" where a dataset was organized into 5 types of emotional categories and obtained a search accuracy of 67.8 percent. The paper goes on to propose an alternative approach to this model called (MER) music emotion recognition in audio by combining both the standard and melodic audio features in music. There are several models that classify emotional states in dimensions, in particular (Russell, 1980) model is the most adopted model where there are known from the basis of anger, disgust, fear, happiness, sadness and surprise. The method used for the data acquisition in this paper was to use the MIREX mood classification task to model the emotions in 5 types of clusters. Cluster 1: passionate, rousing, confident, boisterous roudy; Cluster 2: rollicking, cheerful, fun, sweet, aimable/good natured; Cluster 3: literate, poignant, wistful, bittersweet, autumnal, brooding; Cluster 4: humorous, silly, campy, quirky, whimsical, witty, wry; Cluster 5: aggressive, fiery, tense/anxious, intense volatile, visceral. Ultimately this data would be trained

to read the wave forms of the songs and perform further emotional analysis to better classify where the songs fit in the 5 clusters. This was done through several parameters listed as, timing, dynamics, timbre, articulation, interval, melody, harmony, toneality, rhythm, mode, loudness, musical form and vibrato. The paper goes to state that these parameters are often difficult to extract from audio signals. The use of machine learning was applied in MER under supervised learning. The goal was to supervise the machine to predict which class the test sample of the song belonged to based on previous models. This models used to train was based on ones that were extracted from a ALLMusic database and were fed into the learning machine to determine it's class. The results showed that the feature vibrato had the highest recognition accuracy in search results of 57.6 percent. The key is that the approach for emotion classification in music based on the combination of both standard and melodic audio features is feasible with machine learning. With a bigger dataset and more resources I could see this perspective on search to be an applicable way for tagging music by the emotions is can invoke.

**5 Evolving A Team In A First-Person Shooter Game
By Using A Genetic Algorithm**

6 Summary 6

7 Summary 7

8 Summary 8

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