International Journal of Computer Vision and Signal Processing, 5(1), 23-30(2015) ORIGINAL ARTICLE

Personnel Recognition in the Military using Multiple Features

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Abstract

This paper presents an automatic, machine vision based, military personnel identification and classification system. Classification was done using a Support Vector Machine (SVM) on sets of Army, Air Force and Navy camouflage uniform personnel datasets retrieved from google images and selected military websites. In the proposed system, the arm of service of personnel is recognised by the camouflage and the type of cap badge/logo of a persons uniform. The detailed analysis done include; camouflage and plain cap differentiation using Gray Level Cooccurrence Matrix (GLCM) texture features; Army, Air Force and Navy camouflaged uniforms differentiation using GLCM texture and colour histogram bin features; plain cap differentiation using Speed Up Robust Feature (SURF) on the cap badge. Correlation-based Feature Selection (CFS) was used to improve recognition by selecting discriminating features, thereby speeding the classification process. With this method success rates recorded during the analysis include 94% for camouflage appearance category, 100%, 90% and 100% rates of plain and camouflage cap categories for Army, Air Force and Navy respectively. Similarly, using SURF features on the cap badge in the top region of the segmented human part of top and bottom; the plain cap badge of the military personnel was accurately categorised. By this, we have shown that the proposed method can be integrated into a face recognition system, which recognises an individual and determine the arm of service the person belongs. Such a system can be used to enhance the security of a military base or facility. Substantial analysis has been carried out and results after comparison with two other techniques prove that the proposed method can correctly classify military personnel into various arms of service. Accurate recognition was recorded with the proposed technique.

Keywords: Multi-class classification, military personnel recognition, support vector machines, object recognition, surveillance system, correlation-based feature selection.

ISSN: 2186-1390
http://www.ijcvsp.com

Article History:
Received: 5 May 2015
Revised: 15 July 2015
Accepted: 6 September 2015
Published Online: 7 September 2015

1. INTRODUCTION

Current security challenges such as impersonation, disguise, information and identity theft etc have made it imperative for organisations and individuals to setup surveillance systems to help improve security. It is not strange that military environments are under serious threats on daily basis from terror groups or organisations. These terrorists seek ways to destroy a country's military force (security base): who help defend against domestic and foreign enemies. Suicide bombing, information gathering and leakages, insider attack etc are various ways these terrorists attack military organisations. It is therefore necessary for the military to setup a personnel recognition system to help detect: **(a)** particular uniform type a personnel is wearing and determine the number of persons wearing that particular type of uniform; **(b)** number of personnel present in the environment; **(c)** extra and sound alert that more than expected personnel is/are present in the environment; **(d)** less than expected personnel present and determine if

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the personnel is absent, thereby notify the authority of absent without leave (AWOL) incident. There is the need therefore for an automated system to recognise military personnel in the military camps or environments to check the inflow of persons or personnel in and out of the environments so that various threats as mentioned above can be minimised or eliminated. To this end, we implemented a military personnel recognition in [1]. Personnel was categorised using texture, colour and surf features. This paper is a revised and expanded version of a paper entitled [Military personnel recognition system using texture, colour, and SURF features] presented at [SPIE Defense and Security conference, Baltimore, USA. May 5-9, 2014].

Remaining sections of this paper are arranged as follows: section 2 look at some related literature, section 3 will cover the study outline while support vector machine is briefly explained in section 4. Experimental results are discussed in section 5 and finally conclusion is presented in section 6.

2. RELATED WORKS

Many works have been done to recognise humans or objects using appearance attributes. Appearance of a person is the visible foreground image after background subtraction [2]. Similarly, appearance-based methods rely on clothes, visual parts or perceptual principles to extract features for object recognition [2, 3]. Texture on the other hand, contains structural arrangement of a surface and its relation with the environments [4]. Therefore, texture and colour information will be considered as features for classification in this paper. Gray Level Co-occurrence Matrix (GLCM) which is described as a descriptive texture features will be used as feature in this paper because of its popularity and simplicity [4, 5, 6, 7, 8], also it has been used by many for classification tasks. Colour, texture, shape etc features can be used as descriptors for appearance based object recognition [9, 10, 11]. In [5] using dendrogram as a classifier and GLCM mean as feature, camouflaged object were recognised in a defence environment. Four GLCM texture features fused with non-singleton dimension recognised objects in [6]. In [9] texture combined with YCbCr colour transformed features retrieved image from image sets. Partial Least Squares helped reduce dimension and improve recognition on colour, texture and edge information [10] for human recognition. In [11] edge features and differential image detection technology recognised targets. In [12], semantic and fourier local binary pattern (LBP) features was proposed for human detection. Experimental was compared with histogram oriented gradient (HOG) and covariance tensor feature (COV) descriptors; result shows LBP outperforms both feature techniques. In [13], two sets of edge-texture features, Discriminative Robust LBP (DRLBP) and Ternary Pattern (DRLTP), was proposed for object recognition. Investigation shows the limitations of LBP and its variants; hence, the new feature sets of DRLBP and DRLTP. In solving partial occlusion problem,[14] proposed the combination of HOG and LBP as the feature set for human detection. In [15], C4 was proposed for human detection using contour cues, cascade classifier and census transformed histogram (CENTRIST) descriptor. Authors claimed that C4 is extremely fast for human detection compared to HOG and local binary pattern (LBP). In order to eliminate the false alarm associated with human recognition [16] proposed a background modeling algorithm using fussy logic for accurate foreground segmentation. In [17] the role of face familiarity and motion was examined. It was found that both roles promote recognition in difficult situations. In the paper [18], four different feature techniques were used to recognise and estimate the pose of full body of a person. Similarly, [2] used incremental SVM as a classifier on colour and thirteen Haralick texture features from RGB of segmented body parts (head, top, bottom) of foreground image for an on-line human recognition system. Since [2, 18] categorised humans, we compared our technique with both techniques, results shows improved recognition using the proposed feature sets. Similarly, we showed that the cap badge in the top region of the military person can recognise a personnel arm of service. Since the top region alone can help categorise the personnel it means that it can be integrated into a face recognition system that recognise a particular personnel and at the same time determine the arm of service the person belongs. This system can also do military personnel arm of service persons count which will help check if a particular personnel is present or absent within a particular arm; hence, check if more service personnel is present in the environment or see if a service personnel is on AWOL.

GLCM texture implementation [19] was used to extract texture features, while 256 colour bin histogram will compute the colour feature used in this work. These features; texture, colour plus the Speed Up Robust Feature (SURF) will be used as descriptors for the appearance-based personnel recognition in the military environment which is the focus of this research. Classifications done using Sequential Minimal Optimisation (SMO) Support Vector Machine (SVM) [20, 21] as classifier on multi-category task of Army, Air Force, Navy caps into camouflage and plain respectively; secondly, camouflage appearance classification into Army, Air Force and Navy respectively. In order to improve recognition accuracy, Correlation-base Feature Selection (CFS) was used to select discriminative features and improve recognition results. After the categorisation into camouflage and plain caps SURF feature was used to categorise the plain cap badge into Army, Air Force and Navy accordingly. Similarly, the camouflage category was classified using colour and texture features.

Contributions made includes:

- Camouflage service personnel classification in the military
- Using top region alone for categorisation

- Right feature combination for improved recognition accuracy

3. SYSTEM OUTLINE

The system consists of image pre-processing and personnel recognition. The block diagram of the proposed system is illustrated in figure 1 for a quick overview and for the purpose of clarity.

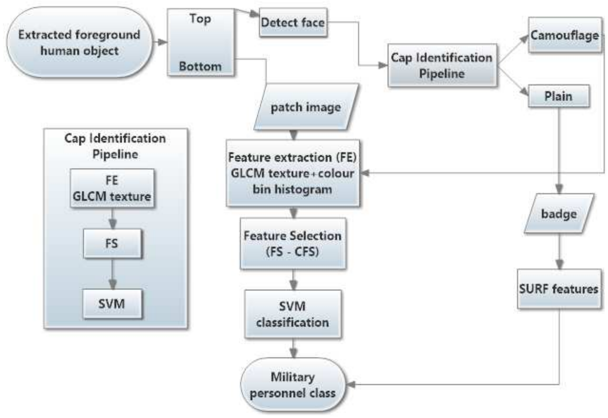

Figure 1: An overview of the proposed method

3.1. Pre-processing, feature extraction and selection

Initially the sample image is segmented to obtain the foreground object by using a people detection algorithm [22] (see figure 2) and the grabcut algorithm [23] (see figure 3).

Figure 2: Detected people results

Figure 3: Segmented foreground images using grabcut

The foreground of the detected and extracted human image is segmented into two parts namely; top and bottom (see figure 4).

Figure 4: Segmented Body Parts results

The bottom segment and the extracted cap is partitioned into equal patches of size 50 x 50 pixels (see figure 5).

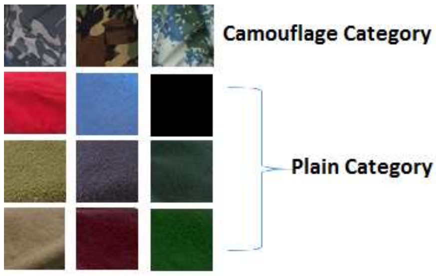

Figure 5: Sample example of Image patch

3.1.1. Feature Extraction

Features are extracted from the selected patch (figure 5) for further analysis. Specifically colour and texture features are extracted from the patch of the segmented human body and used for appearance based categorisation. The colour and texture features extracted are as follows:

1. Hue colour histogram: We calculate one dimensional colour histogram with 256 bins from the hue colour channel.
2. GLCM texture features: Initially, a GLCM was derived for each patch using the MATLAB implementation of GLCM, "graycomatrix". Twenty two statistical texture features were extracted from the GLCM representation of the image patch. The texture features extracted from the GLCM matrix are listed as follows:

- Contrast, Correlation, Energy, Sum of squares: variance, Sum of average, Sum of variance, Sum of entropy, Difference of variance, Difference of entropy, Information measure of correlation, Information measure of correlation 2 as defined in [4]
- Autocorrelation, Cluster prominence, Cluster shade, Dissimilarity, Entropy, Homogeneity, Max probability as defined in [8]
- Inverse difference normalised, Inverse difference moment normalised as defined in [7]
- Correlation, Homogeneity as defined in [19]

The 256 colour bins was combined with the 22 texture features for the appearance based image categorisation. It is noted that the original RGB colour representation is first converted to the HSI colour space before bin values are extracted from the H channel as features used for recognition.

From the image patches (figure 5), we observed similarity of patterns but differences in colour between Army and Air Force camouflage and similarity of colour and differences in patterns between the Army and Navy camouflage. But there appears to be obvious differences in texture between camouflage and plain caps; hence the use of the proposed features.

3.1.2. Feature Selection

To improve recognition accuracy and reduce the feature dimension and processing time, the discriminative features for classification were selected. It is noted that feature selection helps to improve machine learning. There are two approaches to feature selection; wrapper based and filter based approaches [24]. The method adopted here is the filter based approach CFS in Weka. We chose CFS based approach as it performed better than the wrapper based approach and is not algorithm specific [24]. CFS filter algorithm helps to rank feature subsets according to the correlation based on the heuristic "merit" as reported by [2]. In [2] CFS is reported as:

$$M_s = \frac{k.\overline{r_{cf}}}{\sqrt{k + k.(k-1).\overline{r_{ff}}}} \tag{1}$$

where k is the number of features selected in current subset, r_{cf} is the mean feature-class correlation for each element of current subset, r_{ff} is the mean feature-feature correlation for each pairwise of element. It begins with empty set and one at a time add features that holds best value. Best first search method is applied to get merit value.

3.2. Personnel Recognition

Data samples were retrieved from google images and selected military websites. We conducted experiments using N image patch of 50 x 50 from the bottom regions of segmented body parts of the foreground image of military personnel wearing camouflaged uniforms and manually labelled it according to the various arms of service. The set of input-output example is

$$(x_1, y_1), (x_2, y_2), ..., (x_N, y_N) \tag{2}$$

where the input x_i denotes the feature vector extracted from image patch i and the output y_i is a class label. Since we are categorising into military arm of service, the class label y_i encodes Air Force, Army and Navy respectively.

4. SUPPORT VECTOR MACHINE

According to [18] SVM is a technique used to train classifiers, regressors and probability densities that is well-founded in statistical learning theory. SVM can be used for binary and multi classification tasks.

4.1. Binary classification

SVMs perform pattern recognition for two-class problems by determining the separating hyperplane with maximum distance to the closest points of the training set. In this approach, optimal classification of a separable two-class problem is achieved by maximising the width of the margin between the two classes [25]. The margin is the distance between the discrimination hypersurface in n-dimensional feature space and the closest training patterns called support vectors. If the data is not linearly separable in the input space, a non-linear transformation $\Phi(.)$ can be applied which maps the data points $x \in \mathbb{R}$ into a high dimensional space H which is called feature space. The data is then separated as described above. The original support vector machine classifier was designed for linear separation of two classes; to overcome this the multi-class support vector machine was developed.

4.2. Multi-class classification

SVM was designed to solve binary classification problems. In real world classification problems however, we can have more than two classes. In the attempt to solve $q - class$ problems with SVMs have involved training q SVMs, each of which separates a singe class from all remaining classes, or training q^2 machines, each of which separates a pair of classes. Multi-class classification allows non-linearly separable classes by combining multiple 2-class classifiers. N-class classification is accomplished by combining N 2-class classifiers, each discriminating between a specific class and the rest of the training set [25]. During the classification stage, a pattern is assigned to the class with the largest positive distance between the classified pattern and the individual separating hyperplane for the N binary classifiers. One of the two classes in such multi-class sets of binary classification problems will contain a substantially smaller number of patterns than the other class [25].

5. EXPERIMENTAL RESULTS AND DISCUSSION

An initial experiment was conducted for the classification of camouflaged uniforms into the three categories, only using the 22 original set of texture features. For the purpose of training and testing the classifier, a total of 510 image patches (170 each from each type) was used. Fifty percent of the total sets was used for training and fifty for testing. A low classification accuracy of 71% was recorded. A feature selection using CFS of 9 features, maintained an accuracy figure of 68%. The above experiments concluded that the texture features only cannot be effectively used for the uniform type classification. Although increasing the training set and test set could lead to higher efficiencies a significant improvement of accuracy cannot be expected using texture features only. Including the colour features can result in an improved classification accuracy.

In the second set of experiments a total of 256 colour bin values were extracted and combined with the texture features giving a total of 278 features. However in the classification of camouflaged uniforms into Army, Air Force and Navy categories, CFS [24] was used to select discriminate features from the original 278 feature set of 22 texture features and 256 colour features to a total of 46 features that comprised of 8 texture features and 38 colour features, recording a slight improvement of accuracy to 94% from 92.5% when the full feature set was used. In the classification of the cap type into plain and camouflaged categories, only the original 22 texture features were considered. For each of the camouflaged (i.e. Army, Air Force and Navy respectively) vs the corresponding plain cap classification tasks, respectively 6, 4 and 12 textures features were selected via the use of CFS in the classification process (see Table 1 for a summary of features selected for different classification tasks). In all of the above experiments the classifier used is the SVM classifier.

Table 1: Selected Features using CFS on the proposed feature sets

Appearance	**Army Cap**	**Air Force Cap**	**Navy Cap**
CP,CS,EN,HG, SE,IMC,Bins1,20, 31,33,42,43,45,46, 53,64,67,68,85, 89,90,128,132,149, 151,155,156,157, 159,162,163,165, 168,169,172,173, 174,175,176,177, 202,210,233,252	CT,D,EN, ET,SE,IMC	CT,CR,ET, SE	CT,CR,CP, EN,ET,MP, SA,SE,DV, DE,IMC2, IDMN

Notations used: CP - Cluster Prominence, EN - Energy, HG - Homogeneity, SE - Sum of Entropy, IMC - Info measure of Correlation, CS - Cluster Shade, D - Dissimilarity, CR - Correlation, CT - Contrast, ET - Entropy, MP - Maximum Probability, SA - Sum of Average, DV - Difference of Variance, DE - Difference of Entropy, IDMN - Inverse Diff Moment Normalised.

In order to categorise using the top region alone into Army, Air Force and Navy, at the "Top" part, we do a face detection and select the cap region based on the detected face bounding box. Only the texture features are used for the cap classification; if the classification type is of camouflage class, further analysis is performed using GLCM texture and colour histogram bin features to categorise into Army, Air Force and Navy respectively. Similarly, on the plain cap class using SURF features on the cap badge, classification into Army, Air Force and Navy is performed (see figures 6,7, and 8). Experimental results using the SURF features show accurate recognition at different orientation for the plain cap categorisation figure (9).

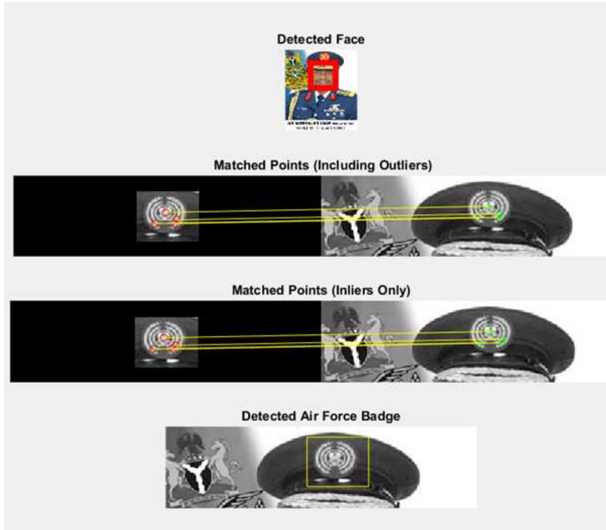

Figure 6: Air Force classification using surf on cap badge

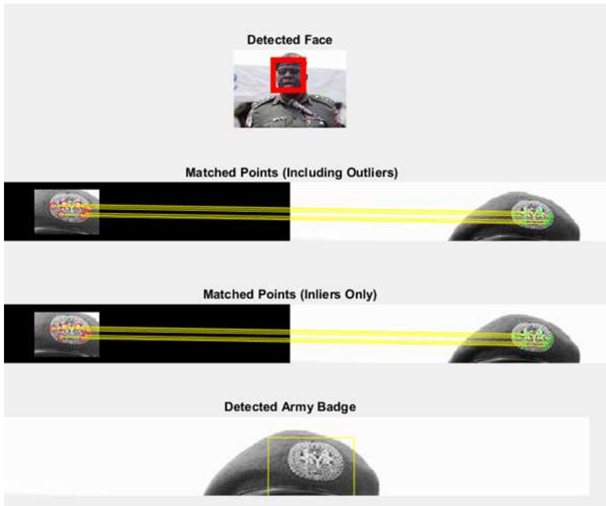

Figure 7: Army classification using surf on cap badge

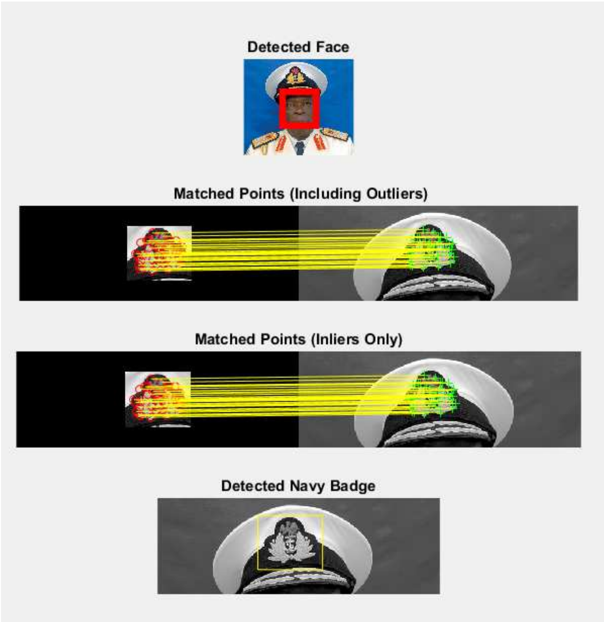

Figure 8: Navy classification using surf on cap badge

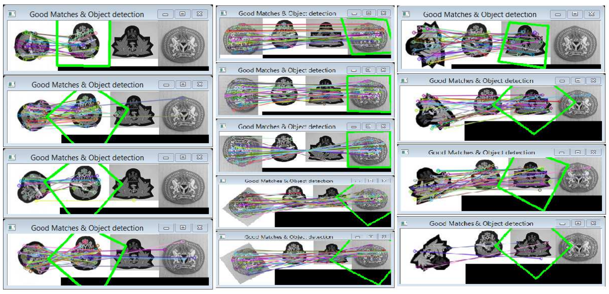

Figure 9: Using SURF to recognise cap badge results

Figure 9 shows cap badges of Air Force, Army and Navy with each serving as query into the three badges in the database. Result at different orientation shows accurate recognition of the three cap badges.

Further experiments were then conducted to investigate the effects of separately using the various colour channels of the HSI colour representation in camouflaged uniform classification, i.e. using H, S and I values separately with their combinations, alongside texture features. The specific feature sets included the following:

- GLCM texture and histogram of Saturation
- GLCM texture and histogram of Intensity
- GLCM texture and histogram of Hue
- GLCM texture and histogram of Hue and saturation
- GLCM texture and histogram of Hue and intensity
- GLCM texture and histogram of saturation and intensity
- GLCM texture and histogram of Hue, saturation and intensity

Experimental results were recorded as shown in table 2

Table 2: Experimental Results for camouflage classification using colour channels and GLCM texture Features

Features Extracted	Recognition Accuracy
Saturation and texture	81.9%
Intensity and texture	77%
Hue and texture	94%
Hue, saturation and texture	89.8%
Hue, intensity and texture	92%
Saturation, intensity and texture	83.5%
Hue, saturation, intensity and texture	89.8%

From table 2 we can see the influence of colour in recognition accuracies.

We compared our technique with the techniques proposed in [18] and [2]. Result of the accuracies are shown in table 3 and figure 10. However, we implemented the technique proposed in [2] twice; **(a).** firstly, we split image patch into three segments and extracted features from each segment; **(b).** secondly, we extracted feature sets directly from the image patch.

Table 3: Recognition accuracies for various techniques using SVM classifier

Features techniques	CFS	Whole	AUC
RGB 32Bin Hist in [18]	70%	86.7%	78%
Normalised 2D Hist in [18]	45%	56.5%	62%
RGB32Bin+Shape Hist in [18]	70%	87%	77.8%
Local Shape in [18]	69%	72.5%	78%
Proposed technique in [2]	71%	71%	82.7%
Feature technique in [2]	72.5%	74%	83%
PropTech - Texture + Hue	94%	92.5%	96.4%

Notation used: PropTech - proposed feature technique, Hist - histogram.

We can see from the above table that our proposed technique recorded highest accuracy on the datasets with normalised 2D histogram with lowest recognition performance (see figure 10).

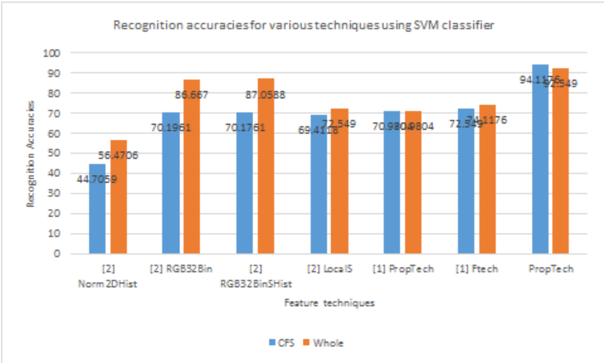

Figure 10: Recognition accuracies for various techniques using SVM classifier

For the purpose of detailed analysis of the performance of the proposed approach, the classification performance is evaluated using the receiver operating characteristic (ROC) curve (see figure 11 below) that helps visualise performance, in detail. In a ROC curve the True Positive Rate (sensitivity or recall) is plotted as a function of the False Positive Rate (false alarm rate) for different cut-off points of a parameter.

True Positive Rate $= \frac{tp}{(tp+fn)}$;

False Positive Rate $= \frac{fp}{(fn+tn)}$;

where, tp denotes the number of true positives (an instance that is positive and classified as positive); tn denotes the number of true negatives (an instance that is negative and classified as negative); fp denotes the number of false positives (an instance that is negative and classified as positive) and fn denotes the number of false negatives (an instance that is positive and classified as negative).

According to [26] an ROC curve visualises the following:

1. It shows the tradeoff between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in specificity).
2. The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate is the test.
3. The slope of the tangent line at a cutpoint gives the likelihood ratio (LR) for that value of the test.

Further the accuracy of performance is defined as:

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn} \quad (3)$$

Accuracy is measured by the Area Under the ROC Curve (AUC). An area of 1 represents a perfect test; an area of 0.5 represents a worthless test. A rough guide for classifying the accuracy of a diagnostic test is the traditional academic point system [26]:

- 0.90-1 = excellent (A)
- 0.80-0.90 = good (B)
- 0.70-0.80 = fair (C)
- 0.60-0.70 = poor (D)
- 0.50-0.60 = fail (F)

In summary the ROC curve shows the ability of the classifier to rank the positive instances relative to the negative instances.

Given the above observations and facts, we plot the ROC graph of the proposed approach vs methods in[2] and [18] when tested on the dataset, in figure 11 below.

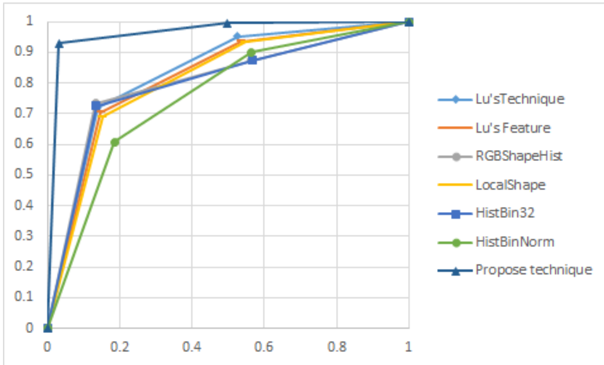

Figure 11: Proposed technique vs methods in[2] and [18]

From the ROC curve 11, we see that the proposed has an excellent performance compared to other techniques with AUC of 96%. [2] technique was good with [18] performing fairly except with one technique which was poor at 62% AUC.

For the purpose of further analysis, the true positives are plotted in figure 12 below.

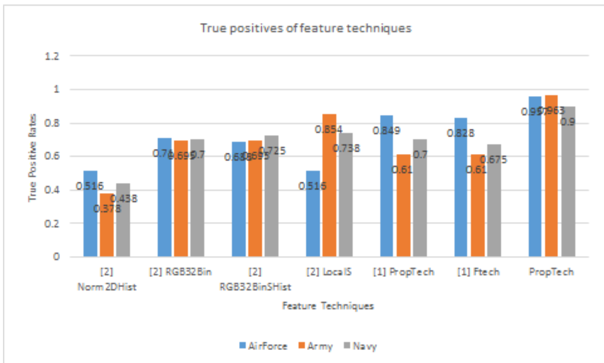

Figure 12: True positives for the various techniques

6. CONCLUSIONS

In conclusion, this paper demonstrates an appearance-based technique that help recognise military personnel's camouflage and determine the arm of service such person belongs. We have established that the top region of the segmented part of military personnel will categorise the service personnel. We have shown that the system can be integrated in a real world face recognition system such that a personnel that is recognised will be checked of the following: appropriate or inappropriate dressing, absence from duty post, impersonation, disguise and completeness or incompleteness of personnel presence in military camp or environment. Few selected features using a filter method; CFS, classified the personnel. Recognition result of 94% for camouflage appearance, 100%, 90% and 100% rates of plain cap and camouflage cap for Army, Air Force and Navy respectively with SURF recording accurate recognition for the plain cap badge at various orientations, was obtained in the entire experiments carried out.

Finally, in the future we will extend the technique to civilian person class to the military recognition system since civilians visit military camps.

ACKNOWLEDGEMENTS

This work was completed with the support of Nigerian Defence Academy, Kaduna, through the Tertiary Education Trust Fund (TETFUND) intervention, Nigeria. The authors was also supported in part by the Loughborough University, United Kingdom.

References

[1] M. E. Irhebhude, E. A. Edirisinghe, Military personnel recognition system using texture, colour, and surf features, in: SPIE Defense+ Security, International Society for Optics and Photonics, 2014, pp. 90900Q–90900Q.

[2] Y. Lu, K. Boukharouba, J. Boonært, A. Fleury, S. Lecœuche, Application of an incremental svm algorithm for on-line human recognition from video surveillance using texture and color features, Neurocomputing 126 (2014) 132–140.

[3] M. Farenzena, L. Bazzani, A. Perina, V. Murino, M. Cristani, Person re-identification by symmetry-driven accumulation of local features, in: Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on, IEEE, 2010, pp. 2360–2367.

[4] R. M. Haralick, K. Shanmugam, I. Dinstein, Textural features for image classification, Systems, Man and Cybernetics, IEEE Transactions on SMC-3 (6) (1973) 610–621. doi:10.1109/TSMC.1973.4309314.

[5] P. Sengottuvelan, A. Wahi, A. Shanmugam, Performance of decamouflaging through exploratory image analysis, in: Emerging Trends in Engineering and Technology, 2008. ICETET'08. First International Conference on, IEEE, 2008, pp. 6–10.

[6] A. S. Shunmuganathan, K.L., Feature fusion technique for colour texture classification system based on gray-level cooccurrence matrix, Journal of Computer Science 8 (12) (2012) 2106–2111. doi:10.3844/jcssp.2012.21.2106.2111.

[7] D. A. Clausi, An analysis of co-occurrence texture statistics as a function of grey level quantization, Canadian Journal of remote sensing 28 (1) (2002) 45–62.

[8] L. K. Soh, C. Tsatsoulis, Texture analysis of sar sea ice imagery using gray level co-occurrence matrices, Geoscience and Remote Sensing, IEEE Transactions on 37 (2) (1999) 780–795. doi:10.1109/36.752194.

[9] C. Bai, W. Zou, K. Kpalma, J. Ronsin, Efficient colour texture image retrieval by combination of colour and texture features in wavelet domain, Electronics letters 48 (23) (2012) 1463–1465.

[10] W. R. Schwartz, L. S. Davis, Learning discriminative appearance-based models using partial least squares, in: Computer Graphics and Image Processing (SIBGRAPI), 2009 XXII Brazilian Symposium on, IEEE, 2009, pp. 322–329.

[11] X. Luo, Q. Luo, B. Han, C. Gao, Special target recognition and location using differential image detection technology, in: Intelligent Human-Machine Systems and Cybernetics (IHMSC), 2010 2nd International Conference on, Vol. 2, IEEE, 2010, pp. 116–119.

[12] Y. Mu, S. Yan, Y. Liu, T. Huang, B. Zhou, Discriminative local binary patterns for human detection in personal album, in: Computer Vision and Pattern Recognition, 2008. CVPR 2008. IEEE Conference on, IEEE, 2008, pp. 1–8.

[13] A. Satpathy, X. Jiang, H.-L. Eng, Lbp-based edge-texture features for object recognition, Image Processing, IEEE Transactions on 23 (5) (2014) 1953–1964.

[14] X. Wang, T. X. Han, S. Yan, An hog-lbp human detector with partial occlusion handling, in: Computer Vision, 2009 IEEE 12th International Conference on, IEEE, 2009, pp. 32–39.

[15] J. Wu, C. Geyer, J. M. Rehg, Real-time human detection using contour cues, in: Robotics and Automation (ICRA), 2011 IEEE International Conference on, IEEE, 2011, pp. 860–867.

[16] A. Mahapatra, T. K. Mishra, P. K. Sa, B. Majhi, Human recognition system for outdoor videos using hidden markov model, AEU-International Journal of Electronics and Communications 68 (3) (2014) 227–236.

[17] D. Roark, H. Abdi, et al., Human recognition of familiar and unfamiliar people in naturalistic video, in: Analysis and Modeling of Faces and Gestures, 2003. AMFG 2003. IEEE International Workshop on, IEEE, 2003, pp. 36–41.

[18] C. Nakajima, M. Pontil, B. Heisele, T. Poggio, Full-body person recognition system, Pattern recognition 36 (9) (2003) 1997–2006.

[19] A. Uppuluri, Glcm texture features (retrieved 15th May, 2013). URL `http://www.mathworks.com/matlabcentral/fileexchange/22354`

[20] J. Platt, et al., Sequential minimal optimization: A fast algorithm for training support vector machines.

[21] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, I. H. Witten, The weka data mining software: an update, SIGKDD Explor. Newsl. 11 (1) (2009) 10–18. doi:10.1145/1656274.1656278.

[22] N. Dalal, B. Triggs, Histograms of oriented gradients for human detection, in: Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on, Vol. 1, IEEE, 2005, pp. 886–893.

[23] C. Rother, V. Kolmogorov, A. Blake, "grabcut": interactive foreground extraction using iterated graph cuts, ACM Trans. Graph. 23 (3) (2004) 309–314. doi:10.1145/1015706.1015720.

[24] M. A. Hall, Correlation-based feature selection for machine learning, Ph.D. thesis, The University of Waikato (1999).

[25] S. Milan, H. Vaclav, B. Roger, Image Processing Analysis, and Machine Vision, 3rd Edition, Cengage Learning, Delhi, 2008.

[26] M. Thomas G. Tape, Interpreting diagnostic tests (retrieved 15th June, 2014). URL `http://gim.unmc.edu/dxtests/roc3.htm`