

Hand Gesture Recognition using a Lattice Autoassociative Memory

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Abstract— This paper presents a Lattice auto associative memory for static hand gesture recognition from a subset of American Sign Language (ASL). After capturing images, the segmentation phase occurs at pixels from the hands using the color injection method. Invariants moments are calculated forming a vector of descriptive characteristics of the gesture at a particular instant of time. This characteristic vector is used by the trained auto associative memory to recognize the gesture performed. The structure of this associative memory is based on computational algebra Lattice. The performance of the gesture recognition method is evaluated in applications of recognize gestures of different hand size, shape and skew angle.

Hand gesture recognition; Human computer interaction; Associative memory.

I. INTRODUCTION

The ability to detect, and recognize people, gestures or objects in the environment is a key pre-requisite for many Ambient intelligence applications. The hand gesture recognition has become popular in recent years for being a natural and suitable interaction device in virtual environments. Many hand gesture recognition methods using visual analysis have been proposed: syntactical analysis, neural networks, the Hidden Markov Model (HMM). However, the development of new structures able to naturally treat this problem of recognition is a broad object of study.

Hand gesture recognition is a complex problem that has been dealt with many different ways. Huang et al. [1] present a system consisting of two phases: feature extraction, based on the model-based method to track hand motion and Fourier descriptor to characterize hand figures, and the recognition phase using a modified 3-D Hopfield neural network to perform a graph matching between the input gesture model and the stored models to recognize the gesture. Already in 2000, Huang et al. [2] developed also another model-based hand gesture recognition system that consists of three phases: feature extraction phase based on a hybrid technique combining spatial (edge) and temporal (motion) information of each frame, training phase that uses the principal component analysis (PCA) to characterize spatial shape variations, the hidden Markov model (HMM) to describe the temporal shape variations and a modified Hausdorff distance measurement to measure the similarity between the feature images and the pre-

stored PCA models, and recognition phase based in the Viterbi algorithm. Yin et al. [3] proposed a method consists of the three steps: segmenting hand images using the restricted coulomb energy (RCE) neural network based color segmentation method, extracted edge points of fingers as points of interest from the segmented hand silhouette; matching a set of points using a robust matching process based on the topological features of the hand; recovering the fundamental matrix and epipolar geometry as accurately as possible. Maurer et al. [4] extend the Hopfield Associative Memory for storing multiple sequences of varying duration.

In the proposed method, hand gesture recognition is divided into three main phases: the detection of the hand's region, the extraction of its features and its recognition. The detection of the hand's region is achieved by using a color injection segmentation technique based in the Hu Saturation (HS) space [5]. The technique is reliable, since it is relatively immune to changing lightning conditions and provides good coverage of the human skin color. In the stage intermediary, the invariants moments are calculated forming a vector of descriptive characteristics of the gesture at a particular instant of time. Finally, this characteristic vector is used by the trained auto associative memory to recognize the gesture performed. The structure of this associative memory is based on computational algebra Lattice.

The proposed gesture recognition system has been trained to identify a subset of American Sign Language (ASL). The signs corresponding to letters A, B, D, H, N, have been chosen to test and the achieved recognition rate is satisfactory.

II. IMAGE PROCESSING

We are working on image statics in PGM format (120x150 pixels). In such images, we are interested in hand gesture recognition. Consequently, hands have been segmented from the image.

A. Hand Segmentation

The image is filtered using color injection in the segmentation of color images in Hue-Saturation (HS) Subspace by means of a Linear Transformation in RGB Space. This method, has been development for Blanco *et al.* [5], add a color vector to the image captured in RGB space with the objective of increasing the separation between the object and

background classes in the HS plane. An example can be seen in Fig. 1.

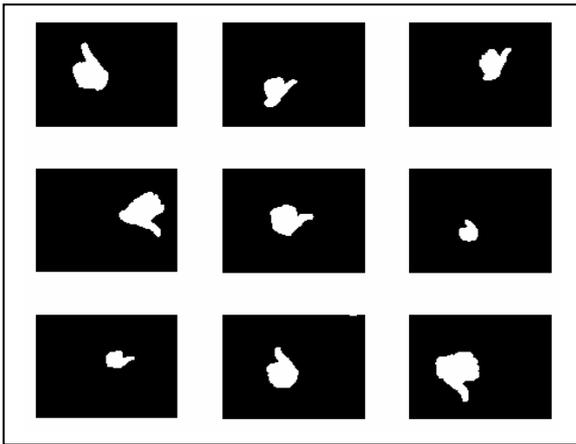


Figure 1. Hand segmented of the gesture corresponding to letter A do ASL.

B. Extraction Gestures

Invariants moments are calculated for to form a vector of descriptive characteristics of the gesture, conserving the geometry features of the image at a particular instant o time.

In particular, Hu [6], defines seven values, computed by normalizing central moments through order three, that are invariant to object scale, position, and orientation. An example can be seen in Fig. 2.

1.9234027e-001	4.0453688e-003	1.9599183e-003	3.1473352e-004	2.4653730e-007	1.6681613e-005	1.7971640e-008
1.9890711e-001	5.2776464e-003	2.7400779e-003	1.2651924e-004	4.5168441e-009	4.9337147e-006	7.4356086e-008
1.9190930e-001	4.5732637e-003	1.5880146e-003	1.2670570e-004	4.9615690e-008	2.4483235e-006	2.7723348e-008
1.9095454e-001	2.3843508e-004	2.3346995e-003	8.7643965e-005	2.9433852e-008	-1.3316620e-006	2.6560261e-008
1.8254910e-001	2.4002872e-003	1.2814243e-003	1.8046667e-004	8.6745123e-008	8.6580191e-006	-2.6129019e-009
1.7308121e-001	5.0915424e-004	4.6345203e-004	4.4898371e-005	3.8656339e-009	6.4699457e-007	-5.1964847e-009
1.9286379e-001	6.4966967e-003	1.1378315e-003	2.9612510e-004	1.6784468e-007	2.3566927e-005	-3.7074223e-008
3.1233498e-001	1.2898774e-002	1.5465407e-001	1.6801571e-001	2.7004981e-002	1.7941773e-002	-2.0614040e-003
1.8246349e-001	3.3471033e-004	1.5370682e-003	1.1531753e-004	4.8383392e-008	1.6412929e-006	4.0191583e-009

Figure 2. Vectors of descriptive characteristics of the hand gesture related to Fig. 1.

III. RECOGNITION USING LATTICE AUTO ASSOCIATIVE MEMORY (LAM)

In recent years, lattice-based matrix operations have found widespread applications in the engineering sciences. In these applications, the usual matrix operations of addition and multiplication are replaced by corresponding lattice operations. Lattice-induced matrix operations lead to an entirely different perspective of a class of nonlinear transformations.

Patterns recognition is an application of LAM model. The concept of this model comes from the theory of image algebra developed by Ritter [7]. The computational basis occurring in the LAM can be found in [8], and the learning rule underlying the theory of computation in the LAM is given by (Eq. 1).

$$W_{XY} = \bigwedge_{\xi=1}^k [y^{\xi} \times (-x^{\xi})] \text{ and } M_{XY} = \bigvee_{\xi=1}^k [y^{\xi} \times (-x^{\xi})] \quad (1)$$

IV. RESULTS AND CONCLUSIONS

Was used Lattice associative memory to store and to recover a set of vectors of descriptive characteristics, thus its implementation has been divided in two phases. First, the vectors or patterns are stored calculating the respective matrix of weights (Eq. 1). Second, beginning in an arbitrary configuration, the memory will become stabilized in the stored pattern that is more nearby of the initial configuration in balance terms. Thus, if it was given an incomplete version or noisy of the stored pattern, the network will be able to recognize the pattern originally stored.

Although this project is not finished, we have some positive results for the recognition of hand gesture static. Some partial results can be seen in Table 1.

Our next work will include techniques of PCA and algorithm genetic for improvement of the perfect recall of noise inputs.

TABLE I. THE ERROR RATE OF THE GESTURE RECOGNITION

Sign	Training	Test
	MSE	MSE
A	0.227x10 ⁻³	9.67x10 ⁻³
B	0.794x10 ⁻³	6.76x10 ⁻³
D	0.730x10 ⁻³	9.01x10 ⁻³
H	0.521x10 ⁻³	9.56x10 ⁻³
N	0.433x10 ⁻³	8.52x10 ⁻³

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REFERENCES

- [1] C. Huang, W. Huang, "Modified 3D Hopfield neural network for gesture recognition", in *Proceedings of International Conference on Neural Networks*, vol. 3, pp. 1650-1655, 1997.
- [2] C. Huang, S. Jeng, "A model-based hand gesture recognition system", in *Machine Vision and Applications*, vol. 12, pp. 243-258, 2000.
- [3] X. Yin, M. Xie, "Estimation of the fundamental matrix from uncalibrated stereo hand images for 3D hand gesture recognition", in *Pattern Recognition*, vol. 36, pp. 567-584, 2003.
- [4] A. Maurer, M. Hersch and A. Billard, "Extended Hopfield Network for Sequence Learning: Application to Gesture Recognition" in *Proceedings of ICANN'05*, LNCS 3696, pp. 493-498, 2005.
- [5] E. Blanco, M. Mazo, L.M Bergasa, S. Palazuelos and A.B. Awawdeh, "Improvement of the Segmentation in HS Sub-space by means of a Linear Transformation in RGB Space", *Innovative Algorithms and Techniques in Automation, Industrial Electronics and Telecommunications*, T. Sobh et al. (eds), Springer, pp.125 -130, 2007.
- [6] M. K. Hu, "Visual pattern recognition by moments invariants", *IRE Trans. Information Theory*, vol. 8, pp. 179-187, 1962.
- [7] B. X. Ritter, J.N. Wilson, J.L. Davidson, "Image Algebra: an overview," *Computational Vision Graphics Image Processing* vol. 3, pp. 297-331, 1990.
- [8] P. Sussner, G.X. Ritter and J.L. Diaz de Leon, "Morphological Associative Memory", *IEEE Trans. Neural Networks* vol. 2, 1998.